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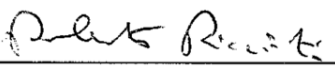
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Organizations in the Digital Transformation:  
essays on the impact of digital data-rich environments on  
organizational capabilities and performance

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## **Introduction**

The huge expansion of contemporary digital data volume is manifest, but the range of this change is probably less evident. The Digital Transformation process is generating a massive expansion of digital data production through the increasing development and adoption of the innovations characterizing Digital Transformation, such as Internet of Things and Industry 4.0.

In the IDC study, “The Digital Universe in 2020” (Gantz & Reinsel, 2012) the hypothesis is that the so called, “digital universe,” will reach the unthinkable number of 40 zettabytes, or the equivalent of 5200 gigabytes, per person, in the year 2020. So, from now to 2020, the digital universe will double each year.

Another interesting insight from the IDC study, is that 68% of the, “digital universe,” in 2012, was basically produced and consumed by consumers, and only a very small part of that digital data is analyzed by firms. The IDC estimation is, that by 2020, one third of the whole digital universe will create value for those organizations able to analyze and extract information from digital data.

In 2015, the IDC report, “FutureScape: Worldwide Big Data and Analytics 2016 Predictions” (Vesset et al., 2015) stated that by 2020, 50% of all business analytics tools will incorporate prescriptive analytics based on cognitive computing. In a nutshell this means that business analytics will cover all three phases of an analytical decision-making process incorporating predictions, decisions, and effects. This is possible only employing a cognitive computing approach to developing analytics that permit analysis of past data in order to make predictions, support decisions, evaluate consequent effects, and re-calibrate the whole algorithm.

Changes in both digital data availability, and analytical tools, are generating a shortage of talents inside organizations. In 2013, the Capgemini report, “The Digital Talent Gap: Developing Skills for Today’s Digital Organizations” (Spitzer, Buvat, Morel, & Kvj, 2013) estimated, that in 2015, of the 4.4 million jobs created around Big Data, only one third of them could be filled.

The same research reports that over 90% of the interviewed organizations stated

they don't possess the necessary skills to cope with the emergent issues of digital transformation such as social media, mobile, and analytics.

Almost 91% of respondents to the IDC SW Survey 2015, reported that of all the possible managerial roles needing to cope with this new landscape, both in terms of data and analytics, the first that requires better business analytics is the Chief Marketing Officer.

This evidence suggests that the development of both digital analytics tools and skills is considered important in the marketing department; the functional area that drives a firm's strategic processes, and directly impacts on a firm's competitive advantage and performance.

At this point, a logical question arises: Can digital skills and analytics really impact on organizational performance?

Some answers to this question are already partially present in the Capgemini-MIT study, "The Digital Advantage: How digital leaders outperform their peers in every industry" (Westerman, Tannou, Bonnet, Ferraris, & McAfee, 2012) What emerges from this research, is that digital leaders, called "Digirati," outperform other organizations with lower levels of digital maturity. Digirati are the organizations that have attained a high level of digital intensity, intended as the level of investment in digital transformation of the company operations and processes, and a high level of transformation management intensity. This latter is measured as the level of the leadership capabilities deployed to drive the digital transformation process.

The digital leaders, or Digirati, with high levels of digital intensity, outperform average industry performance by 9% in terms of revenue indexes (revenue/employees and revenue/assets). Digital leaders that show high levels of leadership in managing digital transformation, outperform the industry average, in terms of profitability, by 26%. (EBIT and Net Profit Margin).

These last empirical evidences, even if derived from a sample of only big companies (81% have more than \$500 million turnover), could suggest that the deployment of digital data and analytics can positively impact organizational performance.

Another important aspect of, "digital universe," is that, basically, it can be reached

by all organizations, and the barriers to accessing digital data are, nowadays, really low compared to the past. Thus the availability of data is no longer an issue, and it cannot create any types of advantage. What could create a possible source of competitive advantage, is the differential access to the information hidden inside the actual overabundance of data.

So the development of analytical skills and processes necessary to extract informative insights from data, and the consequent employment in decision-making processes, can generate an effective differentiation.

Also the, IDC SW Survey 2015, suggests that inside organizations focused on digital transformation, new needs are emerging with regards to the decision-making process. In particular, managers recognize that, “New data sources,” and, “Predictive and actionable insights,” are priorities in the actual scenario.

From an academic point of view, the scenario is quite different. A review of the management literature about these issues, shows the presence of several gaps.

First, there have been no research contribution that have hypothesized a theoretical model explaining why the deployment of digital analytics and data, inside an organization, can lead to superior performance.

Therefore, the study conducted by Capgemini mainly considers big companies in its sample, and this does not well represent the industrial structure of European countries, which are mainly characterized by SME's of smaller size, in terms of both the number of employees and sales turnover.

Another issue is that empirical evidences suggest a correlation between investments in digital transformation, without disentangling the organizational processes, and capabilities that support the positive relationship between digital intensity and performance.

This research wants to mainly address the following research questions that also encompass several theoretical and managerial implications:

1. How the actual over-abundance of digital data can be exploited by organizations to obtain higher performance?
2. What are the organizational systems, skills and capabilities necessary to

obtain such results?

3. Given that attention of managers is limited, they cannot focus on all the possible issues and problems (Ocasio, 1997) what are the most important digital data they have to focus on?
4. Does the deployment of digital data inside organizational decision-making process outperform more traditional and intuition-based forms of information processing?

In order to address the above-mentioned research question four essays are developed.

The first essay aims to delineate a theoretical framework able to explain why the analysis of digital data can drive toward superior results. The framework is based on different theoretical perspectives such as Information Processing view of organizations (Galbraith, 1974; Huber, 1991; Tushman & Nadler, 1978), Dynamic Capabilities perspective (Bruni & Verona, 2009; Eisenhardt, 1989; Teece, Pisano, & Shuen, 1997), microfoundations of Dynamic Capabilities (Teece, 2007) and Strategic Orientation (Gatignon & Xuereb, 1997; Miles, Snow, Meyer, & Coleman, 1978; Zhou, Yim, & Tse, 2005). The resulting theoretical conceptualization and propositions helped in the development of the theoretical framework and hypothesis for the other three studies.

In order to empirically verify the theoretical models, developed to address the research questions, a comprehensive survey was developed, pre-tested and then sent to a sample of 1200 firms derived from a state-of-art database of the Italian limited company. The resulting data frame was made by 251 firms from a wide range of industries and different sizes. A more detailed description of the dataset is provided in the following empirical papers.

The second paper attempts to theoretically explain and empirically verify the impact of customer digital data over the organizational capability to respond quickly to changes in customer needs. In terms of digital channels this paper mainly focuses on Web and Social Media. The overall idea is to verify if the analysis of customer produced digital data can enhance both the organizational responsiveness and performance.

The third paper tries to cope with the last research question about the role of highly analytical decision-making at organizational level, in a context characterized by Mobile technologies. This context is very peculiar because mobile data and analytics permit to develop real-time and location sensitive analyses. In this context we test the role played by highly analytical information processing versus intuitive one.

The last paper addresses a literature gap concerning the role of Social Media in organizational innovativeness. Our results partially contrast some recent empirical evidences suggesting that employing Social Media data to sense technical solutions' information have a negative impact on innovation. Considering the peculiarities of Social Media data, which are mainly episodic, complex and fragmented, we reframe the problem arguing that there is the need of analytics activities and tools in order to make sense of those data. Measuring this theoretical construct, we find a positive effect of this latter on the organizational capability of sense and respond to technological changes.

A specification is needed before approaching the following essays.

This thesis is a collection of research papers developed and written during the Ph.D. course. So all the papers presented in these thesis are firstly developed as research paper and then submitted to international journals. At the time of writing this thesis two of them are accepted in two international journals, but in the next future the aim is to publish all of them.

This specification is needed to explain the structure of this thesis, the repetition of some parts in the different papers, and the co-existence of some of them in international journals, as published research paper, and in the present thesis, as thesis' chapters. The co-existence of them in the present thesis and in international journals is compliant with the editor's policies regarding personal use of the published papers and the multiple/redundant publications clause that explicitly allows the concurrent use in the personal academic thesis.

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## **PAPER 1**

### **Organizational capabilities in the digital era: reframing strategic orientation**

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#### **Abstract**

The digital era is changing consistently the previous marketing scenarios and actual issues have to be addressed in order to close the capabilities gap created by digital innovations. Different authors call for theoretical and empirical contributions that cope with the issues brought out by the digitalization of marketing channels and the consequent ever increasing volume of digital data. This study develops a theoretical framework and propositions through a reframing and reconceptualization of previous theoretical constructs from managerial and marketing literature. The resulting model offers insights about organizational processes and capabilities needed to cope with the actual fast changing, but at the same time, data-rich environment.

**Keywords:** digital era; organizational capabilities; marketing dynamic capabilities; knowledge process; responsiveness; organizational performance.



## 1.1. Introduction

The recent marketing and managerial literature widely recognize that radical technological and environmental changes are transforming marketing scenarios (Day, 2011; Yadav & Pavlou, 2014). The main contemporary issues derived from that literature are: (1) the exploding volume of data (e.g. Kumar et al., 2013; Leeflang, Verhoef, Dahlström, & Freundt, 2014), (2) the new networked and pervasive information technology (IT) or computer-mediated environment (Leeflang et al., 2014; Yadav & Pavlou, 2014) and (3) the consequent fragmentation of market channels and customer touch-points (Day, 2011; Leeflang et al., 2014). All the previous arguments have in common the question about how to manage the information overload deriving from fragmented marketing channels and environments in order to make sense of it and to understand and respond to environmental changes (Day, 2011).

Marketing literature increasingly emphasizes the presence of gaps in organizational capabilities and skills due to the above-mentioned technological and environmental changes (see i.e. Day, 2011; Leeflang et al., 2014) and it does call for coping with these issues especially in digital market context (Yadav & Pavlou, 2014).

This study focuses specifically on the firm-customer and firm-firm interactions (Yadav & Pavlou, 2014) in order to develop a theoretical framework that both takes into consideration the most interesting insights from previous literature and at the same time tries to cope with these more recent issues caused by the switch toward an increasingly digitalized marketplace.

In firm-customer interactions, one of the main issues deals with the enhanced customer visibility, which permits to firms to collect and manage, detailed customer information. This issue can be addressed making the “role of information more explicit in this framework” and extending the Day's (1994) strategic capabilities framework to digital contexts (Yadav & Pavlou, 2014, p. 31).

The increasing speed of environmental changes is driving managerial and marketing literature toward rethinking the theoretical roots of marketing capabilities which are traditionally rooted in resource-based view (see i.e. Day, 1994). But when firms

operate in high-velocity market (Eisenhardt & Martin, 2000) they have to develop dynamic capabilities (DC) in order to obtain at least a series of short-lived competitive advantages (D'Aveni, 1994) or even a sustainable competitive advantage (Teece, Pisano, & Shuen, 1997).

For the above-mentioned reasons there is an increasing attention in theoretically framing and studying marketing capabilities as part of DC perspective, say in the studies on dynamic marketing capabilities framework (e.g. Barrales-Molina, Martínez-López, & Gázquez-Abad, 2013; Bruni & Verona, 2009).

The aim of dynamic marketing capabilities (DMC) framework is to deepen the understanding of relations between marketing and DC and the role of marketing resources and capabilities in developing a sustainable competitive advantage (Barrales-Molina et al., 2013).

What both the traditional DC perspective and the more recent DMC framework have in common is a concern toward the importance of developing market knowledge to sense and seize, or respond to, new opportunities.

As Bruni and Verona (2009) stated: “Dynamic marketing capabilities are specifically aimed at developing, releasing and integrating market knowledge” (p. 102). Firms need both sensing capabilities in order to discover new opportunities and seizing capabilities to exploit them (Teece, 2007). Organizations can sense new opportunity towards a “scanning, creation, learning, and interpretive activity” and they need “differential access to existing information” because “new information and new knowledge (exogenous or endogenous) can create opportunities” (Teece, 2007, p. 1322).

The development of market knowledge “involves interpreting available information in whatever form it appears” (Teece, 2007, p. 1323) and managers need real-time information, especially in high-velocity market, to “adjust [more quickly] their actions since problems and opportunities are spotted” (Eisenhardt & Martin, 2000, p. 1112).

In the actual marketing scenarios the information coming from digital data are becoming central in decision-making process (see i.e. Du, Hu, & Damangir, 2015),

the volume of business-related digital data is ever-increasing, it comes from dispersed sources, with high-level of granularity and it is difficult to analyze (George, Haas, & Pentland, 2014).

But given that attention of managers is limited and they cannot focus on all the possible issues and problems (Ocasio, 1997), research has to deepen the question about which types of information and knowledge have to be taken into consideration to achieve competitive advantage.

Both dynamic capabilities literature and market and strategic orientation literature agree on at least three main issues that organizations have to take into consideration: customers, competitors and technological developments. Firms have to accumulate and filter information “scanning and monitoring internal and external technological developments [...] customer needs and competitor activity” (Teece, 2007, p. 1323). A similar theoretical standing is taken in strategic orientation literature where Gatignon and Xuereb (1997) empirically test the relationship between customer, competitor and technological orientation and product innovation performance.

In the literature reviewed for this study emerges that both strategic/market orientation literature (see Gatignon & Xuereb, 1997; Kohli & Jaworski, 1990; Narver & Slater, 1990) and marketing capabilities literature (see Day, 1994; Jayachandran, Hewett, & Kaufman, 2004; Morgan, Vorhies, & Mason, 2009) already contemplate different theoretical constructs that explain the relations among high information-processing, market knowledge, market responsiveness and organizational performance.

What is missing is a framework that reorganizes and keeps up-to-date these theoretical constructs to respond to the call for adjourning the “strategic capabilities framework to digital contexts” (Yadav & Pavlou, 2014, p. 31) and also take into consideration the initially mentioned issues of the so-called “digital revolution” (Leeflang et al., 2014).

The study’s aims are: (1) develop a theoretical framework that could explain how the digitalization of marketing channels and the consequent massive expansion of real-time data can impact on organizational performance, (2) identify the specific DCs involved and also the processes that act as micro-foundations of DC and (3)

develop a set of theoretical propositions that can be tested in future empirical research.

## **1.2. Increasing volume of digital data and organizational knowledge processes**

The great expansion of Internet, mobile and social media technologies, say the “digital era” (Leeflang et al., 2014), has created a massive volume of digital data available to firms, but this “deluge of data” is challenging the traditional marketing capabilities (Day, 2011, p. 183).

The first step to theoretically reframe the strategic capabilities framework is to define the characteristics that distinguish the data coming from the marketing “digital revolution” (Leeflang et al., 2014) from the previous traditional source of information.

The data characteristics over which both managerial and marketing literature agree are: (1) the ever-increasing volume (Day, 2011; George et al., 2014), (2) the fine-grained nature of the data (George et al., 2014; Yadav & Pavlou, 2014), (3) the different digital sources they come from, such as web, social media and mobile applications (H. Chen, Chiang, & Storey, 2012; Day, 2011) and finally (4) they are real-time produced and potentially analyzable real-time (George et al., 2014; Trainor, Andzulis, Rapp, & Agnihotri, 2014).

These data are making tangible and empirically verifiable the theoretical statement of Einsenhardt and Martin (2000) about managers' use of real-time information in high-velocity market. Real-time digital data permits to deploy real-time data analytics and as a consequence a real-time decision making (George et al., 2014).

On the other hand, in presence of a massive amount of data, organizations risk the so-called “paralysis through analysis” (Peters & Waterman, 1982) due to the overload of data and analysis that slow down decision-making processes. But if organizations deploy proper analytics they can make sense of data and use them strategically (e.g. H. Chen et al., 2012; Davenport, 2006; Kiron & Ferguson, 2012) moreover recent studies have empirically tested the positive impact of analytics over

firm performance (Germann, Lilien, Fiedler, & Kraus, 2014; Germann, Lilien, & Rangaswamy, 2013).

What emerges from organizational learning theory (Huber, 1991; Sinkula, 1994) is that the availability of information does not necessarily increase organizational performance and in order to do so there is the need of structured organizational knowledge processes (see i.e. Jayachandran et al., 2004; Li & Calantone, 1998).

Information processing abilities are critical due to the increasing volume of available market data and these abilities are valuable in order to obtain a competitive advantage because they are difficult to achieve and to imitate (Day, 1994; Hult, Ketchen, & Slater, 2007).

For this reason, the concept of organizational knowledge processes is introduced in the theoretical framework. From the seminal studies on this concept emerges its link with market orientation literature since the authors (see Li & Calantone, 1998) define it as the set of behavioral activities that characterized the market orientation construct. Following organizational learning theory (Huber, 1991; Sinkula, 1994) they define customer and competitor knowledge process as the process consistent in the three steps of acquisition, interpretation and integration of customer or competitor-related information (Jayachandran et al., 2004; Li & Calantone, 1998).

In the same period also the issue of technological developments and changes is analyzed in marketing literature. It is developed the technological opportunism concept which is defined as the "sense-and-respond capability of firms with respect to new technologies" (Srinivasan, Lilien, & Rangaswamy, 2002, p. 48). Technological opportunism concept is conceived, from its origin, as constituted by two distinct capabilities: technology-sensing capability, or the "organization's ability to acquire knowledge about and understand new technology development", and the technology-response capability, which is the "organization's willingness and ability to respond to the new technologies it senses in its environment" (Srinivasan et al., 2002, pp. 48-49).

Analysing both the authors' statements about technology-sensing capability (see i.e. "organization that has strong technology-sensing capability will regularly scan for information about new technological opportunities and threats", p. 48) and the

measurement items this study argues that the most important process that acts as micro-foundation and undergirds this capability is a knowledge process related to technological changes.

### **1.3. Organizational knowledge processes and market performance: the mediating role of responsiveness**

The idea that market-related information processing, say market intelligence (Kohli, Jaworski, & Kumar, 1993), is strongly connected with the firms' market responsiveness dates back to seminal studies on market orientation (Jaworski & Kohli, 1990; Kohli & Jaworski, 1990; Narver & Slater, 1990) which include the concept of responsiveness inside the market orientation construct itself.

Even if different studies have shown a direct positive effect of customer and competitor knowledge process over product innovation (e.g. Li & Calantone, 1998) and even a slightly significant direct effect of knowledge processes over firm performance (Ozkaya et al., 2015), most of the marketing and managerial literature agrees on the mediating role of organizational responsiveness (see i.e. Bhatt, Emdad, Roberts, & Grover, 2010; Homburg, Grozdanovic, & Klarmann, 2007; Wei & Wang, 2011).

One of the first definitions of organizational responsiveness is provided by Kohli and Jaworski (1990): "Responsiveness is the action taken in response to intelligence that is generated and disseminated." (p.6), but similar conceptualization are also in more recent literature where customer-related (competitor-related) responsiveness is defined "as the extent to which an organization responds quickly to customer-related [competitor-related] changes" (Homburg et al., 2007, p. 19) and also "organizational responsiveness [can be defined] as the extent to which a firm responds to market changes" and it "results from firms' gathering, sharing, and interpretation of environmental information" (Wei & Wang, 2011, p. 270).

Also in the framing of organizational responsiveness, in order to consider the third dimension of the strategic orientation framework (Gatignon & Xuereb, 1997), say

the technological changes, the study refers to the literature on technological opportunism (TO). Both in the seminal study on the technological opportunism (Srinivasan et al., 2002) and in the more recent empirical verification of TO impact over organizational performance (C. W. Chen & Lien, 2013; Lucia-Palacios, Bordonaba-Juste, Polo-Redondo, & Grünhagen, 2014), the TO construct is based on two dimensions: sensing and responding capabilities. Thus, technological-responding capability can be defined as “organization's willingness and ability to respond to the new technologies it senses in its environment that may affect the organization” (Srinivasan et al., 2002, p. 49) or likewise as “related to the extent to which an organization is willing and able to respond to new technologies” (Lucia-Palacios et al., 2014, p. 1179).

Given the above-mentioned theoretical statements and empirical verifications the first three propositions can be stated:

*Proposition 1: the use of customer-related digital real-time data has a positive impact over customer responsiveness mediated by customer knowledge process.*

*Proposition 2: the use of competitor-related digital real-time data has a positive impact over competitor responsiveness mediated by competitor knowledge process.*

*Proposition 3: the use of technology-related digital real-time data has a positive impact over technology responsiveness mediated by technology knowledge process.*

The last step for developing a comprehensive theoretical framework is to advance propositions that clarify the impact of the previously mentioned construct over organizational performance.

As Dickson (1992) suggests the “variance in responsiveness” and the exploit of “knowledge and response imperfection” (pp. 75-76) can be sources of competitive

advantage. Also the DC literature has emphasized the importance of being responsive to new opportunities and changes in order to gain competitive advantage (Eisenhardt & Martin, 2000; Teece et al., 1997; Teece, 2007).

Then the positive effect of organizational responsiveness over performance is tested in both strategic management (see i.e. Hult et al., 2007) and marketing (see i.e. Homburg et al., 2007; Jayachandran et al., 2004) literature.

Different empirical studies have shown that customer (and competitor) responsiveness has a positive impact on market performance (see i.e. Homburg et al., 2007; Jayachandran et al., 2004). Recently other studies have empirically verified in more general terms the relation among organizational responsiveness and competitive advantage finding a positive and consistent relationship (e.g. Bhatt et al., 2010; Wei & Wang, 2011).

Also in the case of responsiveness the literature on TO can be, in a way, adapted even if the construct itself analyzes simultaneously the technological sensing and responding capability.

Some recent studies have empirically tested and confirmed the positive, direct and mediated, effect of TO over firm performance (C. W. Chen & Lien, 2013; Lucia-Palacios et al., 2014).

Given the intent to follow the approach of Homburg, Grozdanovic and Klarmann (2007), which analyse the market orientation construct (Narver and Slater, 1990) following the Noble, Sinha, and Kumar (2002, p. 28) suggestion to study it “in a disaggregated manner”, this study tries maintain the same principle and coherence in the following propositions about the relationship of organizational responsiveness and performance.

*Proposition 4: customer responsiveness is positively related with organizational performance.*

*Proposition 5: competitor responsiveness is positively related with organizational performance.*



*Proposition 6: technological changes responsiveness is positively related with organizational performance.*

All the developed theoretical proposition can be visualized in the following figure 1 that represents a hypothesis of the model which can be tested in future research. The model shows in the horizontal axis the different organizational features considered and the vertical axis displays the three strategic orientation dimensions considered.

[Figure 1.1. here]

#### **1.4. Conclusions**

After approximately thirty years from the seminal papers about market orientation, strategic orientation and organizational learning theory, some of the concepts developed in that historical period could be valid yardsticks still in the actual context and they can be reframed to answer to the recent call towards closing the capabilities gap in the digital era. Of course, the context and the rules of the game are changed, but this study shows that reframing and redefining some of those concepts lead to theoretically supported propositions that can answer also to the initially mentioned issues of the digital era.

Future research can enhance the proposed model and investigates, more deeply, inside the organizational processes. Particularly interesting is to deepen the knowledge about how this “deluge of [digital] data” is processed inside the organizations to gain useful insights about the external environment, especially how organizations filter and select the most consistent data and how highly automated and algorithmic analytics influences these processes.

From an empirical point of view, future research should empirically test the propositions in order to verify if the model can consistently explain the impact of the recent data-rich environment and the use of real-time digital data over organizational capabilities and performance.

This study reframes some useful and powerful concepts of the previous marketing and strategic orientation literature in the dynamic capabilities framework in order to move from the resource-based view to another theoretical framework, which is able to fit better with the actual extremely dynamic and changing environment, providing a contribution also to the actual debate about dynamic marketing capabilities. Finally, it brings out some specific processes and capabilities that undergird sense and seizing dynamic capabilities giving the chance to empirically test with future research the impact of these specific micro-foundations over organizational performance and competitive advantage potentially contributing to the debate on micro-foundations of dynamic capabilities.

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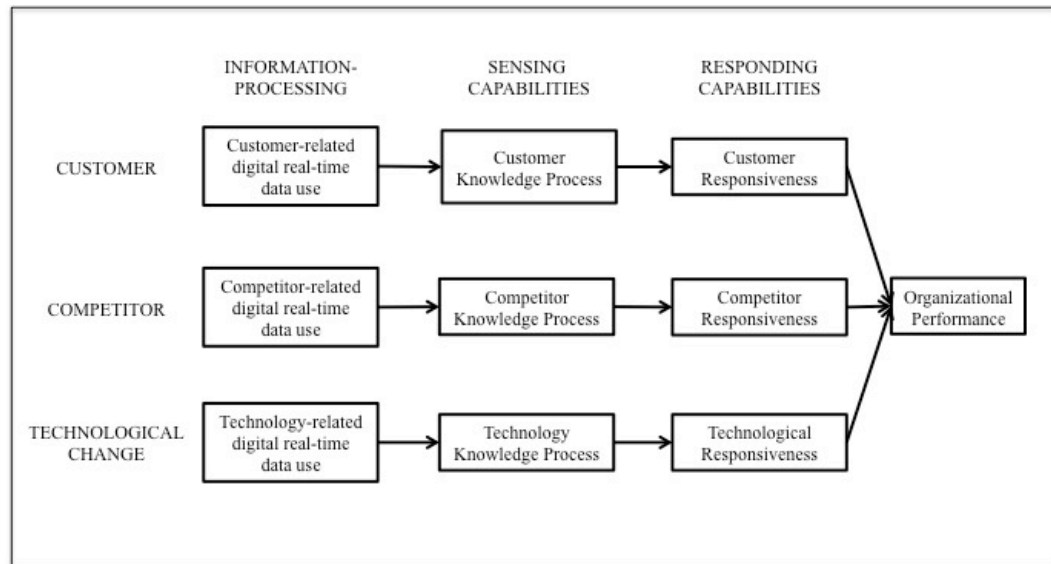
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## Tables and figures

**Figure 1.1.**



## PAPER 2

### **Organizational responsiveness in data-rich environment: the role of digital analytics deployment**

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#### ***Abstract***

Empirical evidence and previous literature on the effect of customer analytics on organizational performance demonstrate contrasting results. The enormous expansion of digital customer-related data, which is accessible almost freely and in real time, has made this a critical issue for contemporary IT and marketing managers. In this study, a research model is proposed in order to empirically test the impact of deploying customer-related digital analytics on organizational responsiveness and performance. The hypotheses were tested employing structural equation modeling analysis in order to shed some lights on the role of customer digital data analytics. The findings show that digital analytics deployment positively and significantly affects organizational performance. Furthermore, they also support the importance of integrating the Marketing and IT functions to improve customer responsiveness in the current scenario of digital transformation.

**Keywords:** digital analytics; analytics skills; marketing/IT integration; customer responsiveness; organizational performance



## 2.1. Introduction

The “digital era” of marketing is leading to significant changes in marketing channels and to new challenges for firms (Leeflang, Verhoef, Dahlström, & Freundt, 2014) because of the massive expansion of customer data available online. According to IDC forecasting, the “Digital Universe” will reach the unbelievable dimension of 5200 gigabytes per person in 2020 (Gantz & Reinsel, 2012).

Data are nowadays dispersed in different virtual environments (e.g. blogs, forums, and social media) and are often freely accessible to firms, potentially in real-time.

Marketers are challenged by this “deluge of data” (Day, 2011, p. 183) relating to customers, as well as the concomitant increasing fragmentation and complexity of the market, and the growing number of customer touch points (Day, 2011).

The focus in the managerial literature on the importance of coping with the rapidly changing environment is not new, and is highlighted by the seminal studies on hypercompetition (D’Aveni & Gunther, 1994) and dynamic capability (DC) (Teece, Pisano, & Shuen, 1997). However, the expansion of social media, the Internet and mobile technologies is causing further acceleration in the rate of change, particularly in relation to firm–consumer interactions (Yadav & Pavlou, 2014).

The proliferation of customer data, marketing channels, customer touch points and media is a double-sided coin. While it creates greater complexity and renders traditional marketing strategies and capabilities obsolete (Day, 2011), it provides the opportunity to improve firms’ capabilities to “sense opportunities” (Teece, 2007, p. 1323) through employing customer analytics and responding to environmental changes.

The effect of customer analytics deployment on performance represents an enduring debate in the managerial literature that is characterized by polarized perspectives. On one hand there is the claim of “paralysis through analysis” (Peters & Waterman, 1982), which asserts that an overload of data and analysis slows the decision-making process, and “heuristic rules can be used to manage uncertainty more

efficiently and robustly than rules based on a broader use of information” (Järvinen & Karjaluoto, 2015, p. 118).

On the other hand recent studies (Germann, Lilien, Fiedler, & Kraus, 2014; Germann, Lilien, & Rangaswamy, 2013; Kannan, Pope, & Jain, 2009) demonstrate that deploying analytics directly and positively affects performance because “analytics can also significantly improve a firm’s ability to identify and assess alternative courses of action [allowing firms to] offer products and services that are better aligned with customer needs” (Germann et al., 2013, pp. 115–116).

The employment of digital customer data can increase the strategy performance of digital business (Oestreicher-Singer & Zalmanson, 2013), but the existing literature still lacks a comprehensive research model that explains the causal mechanisms through which digital analytics impact over organizational performance. Customers’ digital information are fundamental in contemporary marketing strategies (Sawy & Pavlou, 2013), but there is the need to make the “role of information more explicit in this framework”, and to “extend Day’s (1994) strategic capabilities framework to online contexts” (Sawy & Pavlou, 2013, p. 31).

To cope with these gaps this study focuses on “digital analytics” deployment and their effect on customer responsiveness, and market performance. In addition, given the particular context of the use of digital analytics and the consequent need for specific analytics tools (Chen, Chiang, & Storey, 2012) and skills (Leeflang et al., 2014; Royle & Laing, 2014), this study also considers the constructs of digital analytics skills, or the firm’s availability of analytically skilled personnel.

However, information availability and analysis are not sufficient for generating organizational responsiveness without the “interaction of several subsystems within the organization” (Homburg, Grozdanovic, & Klarmann, 2007, p. 19). Also information storage and dissemination linked with a strong customer-oriented culture, are important factors for obtaining customer responsiveness. Thus we also employ marketing/IT integration construct as part of our conceptual model because of its positive effect on organizational information sharing (Peltier, Zahay, & Lehmann, 2013; Tanriverdi, 2005). Finally the level of customer-orientation of organizational

culture is taken into account as a fundamental variable that enhances customer responsiveness (Homburg et al., 2007; Jayachandran, Hewett, & Kaufman, 2004).

This study contributes to the debate in three ways. First it reframes the capabilities framework in the contemporary data-rich environment making the role of customer information more explicit. Then the research model tries to delineate a theoretical framework as detailed as possible to explain the processes and capabilities that acts as antecedents and mediators in the relationship between customer digital data analytics and organizational performance. Finally, it also provides several managerial implications that may support investment decisions about customer-related digital analytics tools and capabilities.

The paper is organized as follow: Section 2 provides the theoretical framework for the study and outlines the development of the hypothesis derived from prior theoretical and empirical literature. Section 3 and 4 present the data-collection process, methodology and analyses, which follow established procedures in structural equation modeling (SEM). Section 5 presents the findings, and lastly Section 6 is devoted to discussion and conclusion.

## **2.2. Theoretical framework**

When the market is highly dynamic (Teece, 1997) and characterized by high velocity (Eisenhardt & Martin, 2000), firms must develop dynamic capabilities (DC) to gain a sustainable competitive advantage (Teece, 1997), or at least to obtain a series of short-lived competitive advantages (D'Aveni, 1994; Peteraf, Di Stefano, & Verona, 2013).

To clarify the role of DCs, Teece (2007) introduced a microfoundations framework categorizing processes and structures that undergird DC. The DC microfoundation perspective and the marketing literature related to information processing and market responsiveness (Homburg et al., 2007; Jayachandran et al., 2004; Li & Calantone, 1998) provides the theoretical background for this study. To complete the overall theoretical framework, and the development of hypotheses, this study

also relies on MIS and marketing literature related with customer analytics.

### *2.2.1. Digital analytics: a necessary clarification*

The first step to define what constitutes digital analytics is to specify which types of digital data and analytics are the object of this study. The study focuses on the all the data that can represent a customer's data footprint (Alaimo & Kallinikos, 2015; Chi, Ravichandran, & Andrevski, 2010), following Alaimo and Kallinikos's (2015) distinction by considering both "online transaction data" and "social data".

The definition of online transaction data refers to all the customer data that represent customer online behaviors (e.g. clicking behavior, page visits, time spent on page) and transactions (e.g. records generated online), but do not represent relationships, opinions, tastes or sentiments (Alaimo & Kallinikos, 2015). Social data can be defined as the "data footprint of social interaction and participation in the online environments of what is now commonly referred to as 'social media'" (Alaimo & Kallinikos, 2015) and represent customer relationships and opinions.

The immense amount of available data, which is particularly widespread in different digital environments, must be managed deploying the right analytics in order to make sense of the data and use them strategically (e.g. Chen et al., 2012; Davenport, 2006; LeeFlang et al., 2014).

Following the literature on business intelligence and analytics (BI&A) (e.g. Chen et al., 2012), and given the extremely different natures of social data and online transaction data (Alaimo & Kallinikos, 2015), this study focuses on web analytics and social-media analytics as representative technologies for digital analytics: the first principally operates on online transaction data and the second on social data.

Web analytics refers to the BI&A 2.0 tools (Chen et al., 2012) developed following the Web 2.0 revolution, which have generated a vast amount of customer data on the web. The use of web analytics allows the understanding of online customer behavior and responses to online marketing stimuli (Järvinen & Karjaluo, 2015)

through performing customer-transaction analysis and market-structure analysis (Bucklin & Sismeiro, 2009; Chen et al., 2012).

The analysis of social-media data requires a distinct set of tools (i.e. social-media analytics), which have already been considered in the previous literature because of the specific features that permit them to run different types of analyses, for example, sentiment analysis relating to customers and competitors (Fan & Yan, 2015), social-networking analysis, and communities and influencer identification (Fan & Gordon, 2014).

### *2.2.2. Digital analytics deployment as microfoundation of sensing capability*

Sensing capabilities refer to a firm's capacity to discover new opportunities using scanning, creative, learning, and interpretative activities (Teece, 2007). Firms need differential access to existing information, fostering research activities and "the probing and reprobing of customer needs" (Teece, 2007, p. 1322). The ability of "interpreting the available information in whatever form it appears [and even] the angst expressed by a frustrated customer" (Teece, 2007, p. 1323) can be considered important information for sensing opportunities.

The development of customer online behaviors, such as leaving comments on social media and rating online products and services, is creating a vast amount of dispersed data from which firms can gain useful information about customers' needs and market trends through digital analytics (Du, Hu, & Damangir, 2015).

Moreover these data are produced almost in real-time permitting to managers that operate in high-velocity market to build "intuition about the marketplace" and "more quickly understand the changing situation and adapt to it" (Eisenhardt & Martin, 2000, p. 1112).

The digital analytics deployment, given the real-time nature of digital customer data (George, Haas, & Pentland, 2014; Trainor, Andzulis, Rapp, & Agnihotri, 2014), can be framed as microfoundational process behind firms' sensing capabilities, grounded in organizational processes devoted to opportunity discovery with the

purpose to scan and monitor technological developments and customer needs (Teece, 2007) to gain competitive advantage.

Previous literature has already tested and verified the positive effect of customer analytics deployment over firm's performance (see i.e. Davenport, 2006; Germann et al., 2014, 2013; Kiron & Ferguson, 2012), but not in the digital context, beside the impact over customer responsiveness has not been investigated yet, leaving unsolved the debate about "paralysis through analysis" (Peters & Waterman, 1982).

Given the previously introduced theoretical and empirical contributions, we hypothesize that digital analytics deployment has a positive effect on performance. Moreover given the real-time nature of digital data, which potentially supports organizational sensing capabilities, we also hypothesize a positive effect over customer responsiveness.

**H1.** Customer-related digital analytics deployment has a positive effect on market performance.

**H2.** Customer-related digital analytics deployment has a positive effect on customer responsiveness.

### *2.2.3. Customer responsiveness and affective organizational systems*

The differential access to real-time information is not the only necessary condition for enhancing organizational responsiveness. Organizational culture also plays a fundamental role in supporting intensive information processing inside companies (Leeflang et al., 2014; Peltier, Zahay, & Lehmann, 2013).

There is evidence that the customer-related affective organizational system – defined as "the extent to which attention to customer needs is anchored in an organization's values, belief structures, and norms" (Homburg et al., 2007 p. 20) – is more

important in driving customer responsiveness than customer-related organizational information processes.

Given the importance of customer orientation in the affective organizational system in enhancing customer responsiveness and increasing performance (Germann et al., 2013; Homburg et al., 2007; Narver & Slater, 1990; Peltier et al., 2013), this study also considers the orientation of the affective organizational system, relying on Homburg et al.'s (2007) definition.

The concept of market responsiveness dates back to the seminal studies on market orientation, and is framed as the firm's responsiveness to market intelligence in relation to customer needs (Jaworski & Kohli, 1990; Kohli & Jaworski, 1990). More recent studies have demonstrated that information processing and market intelligence affect organizational responsiveness, and that organization responsiveness in turn mediates the positive effects of information processing and market intelligence on firm performance (Bhatt, Emdad, Roberts, & Grover, 2010; Hult, Ketchen, & Slater, 2005).

This study focuses on customer-related responsiveness following Jayachandran et al.'s (2004) definition of customer-response capability as the "competence in serving customer needs through effective and quick actions" (p. 220), and recognizes customer-related responsiveness as a critical capability for market performance (Homburg et al., 2007; Jayachandran et al., 2004).

To be responsive, organizations need to adapt rapidly (Haeckel, 2013) to match changing customer needs and market environment.

From the perspective of the DCs microfoundations, customer responsiveness can be seen as the firm's competence that undergirds its capability to seize opportunities (Teece, 2007) and part of its "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997, p. 516). This ability is particularly necessary in high-velocity markets (Eisenhardt & Martin, 2000).

Considering all the theoretical and empirical premises discussed thus far, we formulated the following hypothesis:

**H3.** Customer-orientation of the affective organizational system has a positive effect on customer responsiveness.

**H4.** Customer responsiveness has a positive effect on market performance.

#### *2.2.4. Enhancing customer-information processing: marketing/IT integration and digital analytics skills*

As previous research suggests, the integration between marketing and IT could lead to various benefits such as enhancing collaboration and information sharing in the organization (Tanriverdi, 2005); higher departmental market orientation (Borges, Hoppen, & Luce, 2009); improving customer acquisition and retention (Brodie, Winklhofer, Coviello, & Johnston, n.d.); and developing specific marketing capabilities that positively affect organizational performance (Trainor, Rapp, Beitelspacher, & Schillewaert, 2011).

Today, the need to integrate marketing and IT is even more pronounced given the differences between traditional marketing practices and digital marketing practices. Marketers face many new challenges brought by the computer-mediated environment (Yadav & Pavlou, 2014). The digital era is changing the structure and content of marketing managers' job (Germann et al., 2013), and is creating a "talent gap" (Leeflang et al., 2014, p. 8) in analytics skills.

The importance of analytics skills in the digital era is highlighted in Leeflang et al. (2014), who state that "hiring more analytically skilled individuals is seen as a strategic asset" (p. 8). This is even more true in the context of analytics implementation and use, where analytics skills are essential for gaining meaningful insight from analytics tools (Järvinen & Karjaluo, 2015). In the context of marketing analytics, both tacit individual-level skills and more technical-related skills are directly related with a superior deployment of analytics and indirectly to performance (Germann et al., 2013), beside we expect that in presence of digital analytics skills



also the speed of spotting changes increase; then following all the previous theoretical stances we hypothesize:

**H5.** Marketing/IT integration has a positive effect on customer orientation of the organizational affective system.

**H6.** Marketing/IT integration has a positive effect on customer responsiveness.

**H7.** Digital analytics skills have a positive effect on digital analytics deployment.

**H8.** Digital analytics skills have a positive effect on customer responsiveness.

The research model is presented below (Fig. 2.1) and it visualizes the hypothesized relations among theoretical constructs and the fundamental role of customer responsiveness as mediator of most hypothesized relations.

[Figure 2.1 here]

## **2.3. Research methodology**

### *2.3.1. Sample and data collection*

The survey is developed both employing constructs already present in managerial and marketing literature, and a new scale for measuring the digital analytics deployment in customer-related activities. The survey is developed, pre-tested and refined in collaboration with eight experts, four from academia and four from consultancy and business environment.

The target respondents for this research were obtained from a state-of-art commercial database of Italian firms (AIDA – Bureau Van Dijk). The authors identified as potential respondents, managers with roles of responsibility in marketing or related activities. The focus is on marketing managers because they are most involved in, and informed about, activities related to customer sensing and responding (Roberts & Grover, 2012). The frame of potential respondents was a sample of 1200 firms across a broad spectrum of industries, geographical locations, and dimensions.

The respondents were assured of compliance to Italian privacy laws providing anonymity and aggregate use of data. As incentive to participate, the authors offered to provide them with a report with the study results and extended an invitation to attend a workshop related to the study. The responses were collected in approximately twelve weeks, and one phone follow-up was performed to test for non-response bias. A total of 251 responses were received, which equaled a response rate of 20.9%. Of the 251 questionnaires received, 156 are fully completed, and 95 were partially completed and present missing values; in this latter case missing data treatments are employed to solve the issue (see Section 4).

Organizational respondents represented a wide and equilibrated variety of industries: services (14%); ICT (13.6%); fashion and clothing (12%); manufacturing (8%); food and beverage (6%); also other industries are present with percentage less than 5% (e.g. pharmaceutical, bank and assurance, automotive, chemical, electronics...). The firm sizes in the sample are measured partially following the E.U. Commission size classes (2003/ 361/EC). Our sample displays 10.2% of micro firms, with a number of employees between 0 and 9; a 23.6% of small firms (10-49 employees); a 29.6% of medium firms (50-249 employees); and a 36.6% of large firms (>250 employees).

### *2.3.2. Measures*

Almost all the multi-item scales used were adapted from previous literature, and have been tested in survey research. All were based on a 7-point Likert-type scale

(ranging from 1 = “strong disagree” to 7 = “strong agree”). Constructs, measurement items, Cronbach’s alpha (CA) and Composite Reliability (CR) scores are presented in Table 2.1.

To measure digital analytics customer-related deployment, the authors developed a specific multi-item scale adapted to each type of digital analytics considered. To test the use of customer-related web and social-media analytics, this study partially follow previous approaches for measuring technology use (Jayachandran, Sharma, Kaufman, & Raman, 2005; Trainor et al., 2014). Instead of creating a single-item index, we used a multi-item scale based on the possible functions and use of digital analytics that emerged from practice-oriented literature analysis and the collaboration of eight experts, four from consultancy and business environment, and four from academia. The items, tested with exploratory factor analysis (EFA), demonstrate consistent loading only on one factor and then we test them in the confirmatory factor analysis (CFA) and Cronbach’s alpha.

[Table 2.1 here]

## **2.4. Data analysis**

Given the aim of verifying theoretical hypothesis derived from literature, this study employs correlation-based structural equation modeling (CB-SEM), which is more suitable in theory testing in case of not too complex model, with sufficient large number of observations (Hair, Hult, Ringle, & Sarstedt, 2014).

### *2.4.1. Preliminary data analysis*

Before the empirical analysis we conduct some preliminary analysis to analyze and solve the issue of missing data and to test for non-response, common method bias and multicollinearity.

Given the recent suggestion in management research of avoiding the practice of simply reject missing data observations to analyze fully completed set, or the employment of basic techniques such as Listwise Deletion and Pairwise Deletion (Karanja, Zaveri, & Ahmed, 2013; Newman, 2014), we employ 3rd generation techniques to manage our missing data. Using Little's test we found that our missing data follow the missing completely at random (MCAR) assumption (Chi-Square (91) = 90.79,  $p = .49$ ). Given the MCAR distribution we employ Full Information Maximum Likelihood (FIML) remedy in structural equation model analysis, which produces unbiased parameters estimates (Karanja et al., 2013) and is highly recommended remedy for MCAR missing data in management research (Karanja et al., 2013; Newman, 2014).

To test for non-response bias we employ the widely accepted method of comparing early and late respondents, given no statistically significant differences emerged between the two, we are assured that non-response bias was not an issue for this research.

With regards to common method variance (CMV), from the beginning of the data collection, we managed to control for this issue following some of the best-practices for management research suggested in Woszczynski and Whitman (2004); we assure anonymity to the respondents and avoiding items' social desirability, demand characteristics, and ambiguity (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Once data were collected we test for common method bias employing Harman's single-factor test (Podsakoff et al., 2003; Woszczynski & Whitman, 2004) which shows that the variance explained by the single factor in the unrotated factor matrix is 34% largely below the 50% threshold.

Moreover, employing confirmatory factor analysis (CFA) we compare the research model with a model where all items load on one construct; the last one displays unacceptable fit indexes. These results suggest that common method variance is not a significant issue in this study.

Finally multicollinearity is assessed with two steps, first all AVE are above 0.5 except one (see Table 2.2), which is quite near (0.44), then the Variance Inflation Factor (VIF) are in a range between 1.13 and 1.97, safely under the suggested

threshold of 5 (Hair, Sarstedt, Ringle, & Mena, 2012).

#### *2.4.2. Reliability and validity*

In Table 2.1 are presented the Cronbach's alpha (CA) and Composite Reliability (CR) scores. All the CA and CR scores, except for COA, are above 0.7 suggesting adequate construct reliability (Hair, Black, Babin, & Anderson, 2010). The COA construct displays a CA=0.67, which is slightly below the threshold, but it could depend also from the low number of items and is quite far from unacceptable thresholds (Peterson, 1994). To support constructs validity some evidences are presented. First all the item loadings are above 0.5, then CR are above 0.7 in almost all cases, only COA has a CR=0.69 which is pretty near the threshold and far from being unacceptable (Fornell & Larcker, 1981). Besides all AVE are above 0.5 (see Table 2.2), except also in this case for COA (0.44).

Lastly the CFA displays adequate fit indexes suggesting an adequate construct validity of the measurement model  $\chi^2$  of 264 with 174 df and CFI=0.97; TLI=0.96; RMSEA=0.047; SRMR=0.050;  $p=0.000$ .

[Table 2.2 here]

### **2.5. Findings**

The CB-SEM results (see Fig. 2.2) show that the model has a good fit with data:  $\chi^2$  of 271.37; df=180; CFI=0.97; TFI=0.96; IFI=0.97; RMSEA=0.047; SRMR=0.061;  $p=0.000$ .

The H1 and H2 hypotheses are central in the debate about the importance of customer-related digital analytics deployment, postulating positive relationships between DACD and organizational performance and responsiveness. Only H1 finds support in the resulting model ( $\beta = 0.15$ ;  $p < 0.05$ ) instead H2 is not supported by

results showing contrasting sign respect to theoretical hypothesis ( $\beta = -0.05$ ) and a not significant p-value.

As empirically verified in non-digital context, the model supports the H3 that claim positive relationship between customer orientation of the affective organizational system and customer responsiveness ( $\beta = 0.67$ ;  $p < 0.05$ ). Likewise, customer responsiveness is positively related to market performance (H4) in significant way ( $\beta = 0.50$ ;  $p < 0.01$ ).

The model confirms a quite interesting role of Marketing-IT integration in supporting customer orientation (H5;  $\beta = 0.05$ ;  $p < 0.05$ ) and customer responsiveness (H6;  $\beta = 0.10$ ;  $p < 0.05$ )

Finally, the model partially supports the central role of digital skills, which is intensively debated in the literature in terms of organizational gap to fill (Day, 2011; Royle & Laing, 2014; Spitzer, Buvat, Morel, & Kvj, 2013). The H7 claims that digital skills positively affect the deployment of customer related digital analytics and it finds support in the model ( $\beta = 0.70$ ;  $p < 0.001$ ). Whilst the H8, which suggests a positive relation between digital skills and customer responsiveness, is not supported because the sign is opposite ( $\beta = -0.08$ ) respect to the theoretical hypothesis and p-value is greater than 0.05.

## **2.6. Discussion and conclusion**

This study has attempted to shed some lights on the role of customer-related digital data and analytics in the organizational framework of sensing and responding capabilities. Besides it empirically finds a positive relationship between the employment of customer digital data in organizational activities and market performance. This relationship is framed in a detailed research model that displays the other organizational capabilities, skills and integration mechanism necessary to support the deployment of digital customer data inside organizational processes and decision-making.

### *2.6.1. Theoretical implications*

This study contributes to the existing literature in several ways. First it reframes the debate about customer information processing in the actual context of customer data-richness or even over-abundance of digital data. Moreover, this study theoretically roots the research model in the micro-foundations dynamic capabilities perspective in order to contribute to a literature that still includes very few empirical studies.

Then it contributes to customer analytics literature explicitly investigating the role of customer digital data and analytics.

The huge growth of customer digital data and related digital channels (social media, e-commerce, blogs...) has led to an extraordinary growth of the analytical tools and practices to extract value from customer digital data, but the literature was still lacking of a research model that theoretically frames the relationships between customer digital data deployment and organizational performance. Previous literature suggests that the mere availability of digital customer data is not sufficient to obtain superior performance. The deployment of digital analytics tools and activities acts as microfoundation of sensing capabilities that permit to respond more quickly to customer changes obtaining competitive advantage. However, our empirical evidences do not support this theoretical relationship.

In the resulting model the relationship displays a negative sign and it is not significant, instead the direct relationships between customer digital analytics deployment and market performance is positive and significant. This finding may suggest the presence of a plausible “paralysis through analysis” (Peters & Waterman, 1982), but of course further research has to be developed to confirm this weak signal.

Finally, from a theoretical point of view, the positive and significant direct relationship between digital analytics deployment and performance suggests that not necessarily market performance can be reached focusing on responding to customers’ changes and on seizing new customer-related opportunities. But even “lighter” forms of tuning to customer needs can drive performance; indeed, also this theoretical speculation has to be further investigate.

### *2.6.2. Managerial implications*

The extraordinary growth of the so-called “Digital Universe” has led managers, especially in marketing and strategic related functions, to question about how extracting value from customer digital data. Besides the other central issue regards the impact of digital analytics tools and activities on performance. This study can contribute providing some interesting managerial insights.

First of all, the empirical evidences support a positive impact of digital analytics deployment on market performance reassuring about the importance of investing managerial attention and organizational budget on this issue. Then even the digital tools are an important part to support analytics activities and process, the importance of individual skills is reasserted. To support digital analytics deployment, analytical skills of personnel are fundamental; an eventual digital skills gap has to be filled in conjunction with the development of customer digital analytics activities.

From another point of view digital analytics deployment has not to become a hype. The model in this study confirms the central role of customer responsiveness as antecedent of firm market performance and, at the same time, the non significant effect of digital analytics deployment on responsiveness. Then also other organizational features have to be considered in the actual scenario of over abundance of digital customer data. The customer orientation of organizational culture and the marketing/IT integration significantly contribute to organizational responsiveness confirming their importance in managers’ agenda.

### *2.6.3. Limitations and future research directions*

Although this study contributes in shedding some lights on a central issue of the current managerial debate, it is constrained by some limitations. First the employment of self-reported perceptual data based on single key informant could weaken the internal validity of the study. Several precautions are taken to attenuate common



method variance; anyway given the importance of checking for inter-rater validity future research should implement a sampling of multiple respondents for each firm. Then, as already said before, the empirical evidences suggest that further research has to be done to address at least two issues. The negative and, almost, non significant relationships between digital analytics deployment and responsiveness paves the way to a plausible paralysis effect of too much customer data analysis, but there is the need to find significant empirical evidence of it. The other issue regards the direct, positive, and significant effect of customer-related digital analytics deployment on market performance. This insight suggests, as said, a possible alternative employment of customer digital data, different from the theoretical hypothesis derived from the dynamic capabilities perspective. The relationship between sensing and responding to customer changes and new opportunities seems less central, at least in the digital context, than theoretically hypothesized. Further investigations should address this issue to shed some lights on the different mechanisms that connect digital analytics customer-related deployment and market success.

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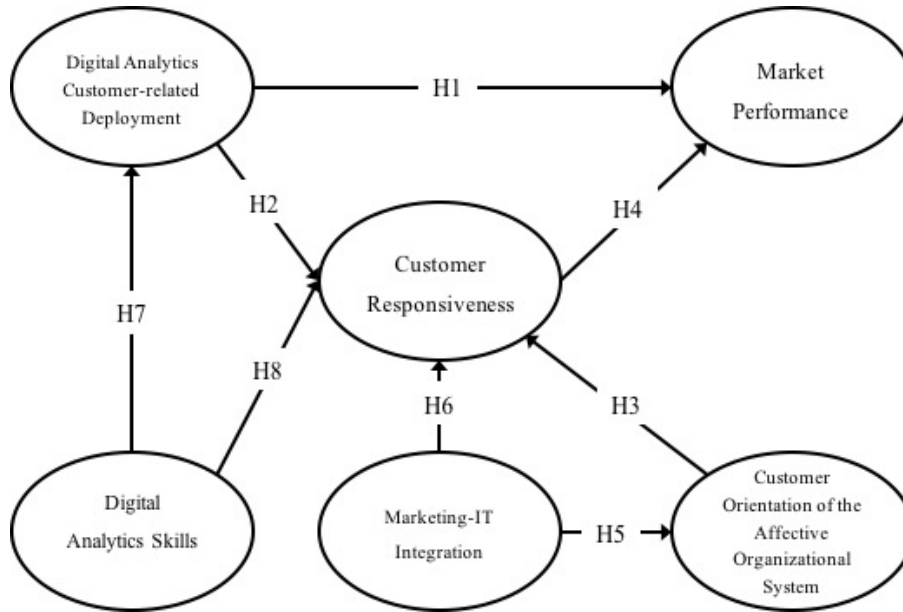
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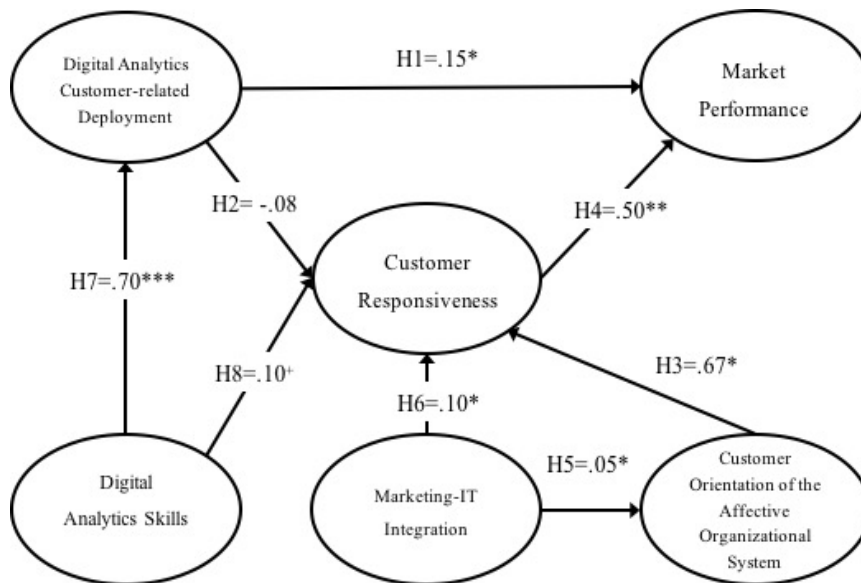
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## Tables and figures

**Fig. 2.1.** Research model



**Fig. 2.2.** CB-SEM model



Fit indexes:  $\chi^2$  of 271.37; df=180; CFI=0.97; TLI=0.96; IFI=0.97; RMSEA=0.047; SRMR=0.061; p=0.000  
 # of cases =226 = # of usable responses; + p<0.1; \*p<0.05; \*\*p<0.01; \*\*\*p<0.001.

**Table 2.1.** Summaries of measurement items.

Construct	Items #	Scale items	Source
Digital analytics customer-related deployment (CA=0.91 CR=0.90 )	DACD 1	We habitually use web analytics tools to collect information about customer. (0.84)	
	DACD 2	Decision-making about customers is supported by web analytics data. (0.93)	
	DACD 3	We habitually use social media analytics tools to collect information about customer. (0.79)	
	DACD 4	Data from social media analytics are crucial in supporting customer-related activities. (0.91)	
Marketing and IT integration (CA=0.93 CR=0.93 )	MII 1	Marketing is involved with IT in setting new project schedules. (0.90)	Adapted from Pel- tier et al. (2013)
	MII 2	Marketing is involved with IT in setting new project goals and priorities. (0.94)	
	MII 3	Marketing is involved with IT in generating new project ideas. (0.97)	
	MII 4	Marketing and IT frequently discuss the quality of the data system. (0.79)	
Digital analytics skills (CA=0.96 CR=0.96 )	DAS 1	Our people are very good at identifying and employing the appropriate web/social media analytics tool given the problem at hand. (0.84)	Adapted from Germann et al. (2013)
	DAS 2	Our people master many different web/social media analytics tools and techniques. (0.94)	
	DAS 3	Our people can be considered as experts in web/social media analytics. (0.96)	
Customer orientation of the affective organizational system (CA=0.67 CR=0.69)	COA 1	We are aware that customers are important factors that influence the success of our company. (0.80)	Adapted from Homburg et al. (2007)
	COA 2	We emphasize customer-related activities and success. (0.85)	
	COA 3	We have a customer-oriented culture. (0.64)	
Customer responsiveness (CA=0.88 CR=0.88 )	CUR 1	We respond rapidly if something important happens with regard to our customers. (0.79)	Adapted from Homburg et al. (2007)
	CUR 2	We quickly implement our planned activities with regard to customers. (0.87)	
	CUR 3	If our customer-related activities do not lead to the desired effects, we are fast at changing them. (0.87)	
	CUR 4	We quickly react to fundamental changes with regard to our customers. (0.88)	
Market performance (CA=0.94 CR=0.94 )		In the last three years relative to your competitors, how has your business unit performed with respect to:	Adapted from Homburg et al. (2007)
	MP 1	Achieving the desired profit and revenue level?* (0.92)	
	MP 2	Achieving the desired growth?* (0.96)	
	MP 3	Achieving/securing the desired market share?* (0.93)	
* Seven-points rating scale anchored by “clearly worse” [1], “competition level” [4], and “clearly better” [7]			



**Table 2.2.** Means, standard deviations, inter-construct correlations, and discriminant validity

Constructs	M	SD	AVE	1	2	3	4	5	6
1. Digital analytics customer-related deployment	5.04	1.67	0.70	<b>0.84</b>					
2. Marketing and IT integration	4.78	1.43	0.76	0.38	<b>0.87</b>				
3. Digital analytics skills	4.48	1.65	0.88	0.66	0.42	<b>0.94</b>			
4. Customer orientation of the affective organizational system	6.48	0.62	0.44	0.15	0.17	0.20	<b>0.66</b>		
5. Customer responsiveness	5.80	1.00	0.65	0.13	0.27	0.25	0.31	<b>0.81</b>	
6. Market performance	4.87	1.21	0.83	0.20	0.23	0.29	0.12	0.27	<b>0.91</b>

1. M=mean; SD=standard deviation; AVE=average variance extracted.

2. Numbers on the diagonal are the square root of AVEs. The other numbers are correlations among constructs.

## **PAPER 3**

### **Analysis or paralysis?**

### **Analytical and intuitive organizational information processing in the mobile technology context**

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#### **Abstract**

The debate over intuitive versus analytical information-processing styles began almost 40 years ago and has led to divergent theoretical stances and empirical results. Most contributions claim that intensive data collection and analysis is too slow and unreliable in highly turbulent and dynamic environments and that intuitive information processing is faster and more effective. Today, the environmental context has changed completely. By employing mobile technologies, people can search for and retrieve information in real time, producing a massive amount of location and time-sensitive data. Through mobile technologies, organizations can now interact with their customers in real time and collect and analyze the data produced by these interactions. This study investigates the previously mentioned debate in actual mobile technological contexts. The results show that intuition is still extremely relevant, but in highly dynamic environment also analytical information processing has positive impact over organizational responsiveness and performance.

**Keywords:** mobile technology · intuition · analytics · environmental dynamism · responsiveness · performance

### 3.1. Introduction

Firms' investments in mobile technology are increasing rapidly and have recently comprised a quarter of their entire digital budgets (Shankar, 2016). In addition, mobile technologies are so widespread "that there are more people with mobile devices than there are with toothbrushes in the world" (Shankar et al., 2016, p. 37).

The rise of the adoption of mobile technology is a challenge that represents an unprecedented chance for organizations in terms of both managing customer relations and gaining customer knowledge.

On the one hand, the diffusion of mobile technologies represents an organizational challenge because of market channel fragmentation and the rapid growth of customer touch points (Day, 2011). Customers have the chance to "perform a number of activities and make decisions on the move" (Shankar et al., 2016, p. 38). They can search and collect information and carry out their decision-making process about an object of interest in real time and in physical proximity to the object itself.

On the other hand, the increase in mobile technology adoption has created a scenario of possibilities linked with the real-time and location-sensitive nature of mobile customer data (Chen, Chiang, & Storey, 2012; Ghose, Goldfarb, & Han, 2013).

Organizations that face a high-velocity market characterized by high dynamism need access to real-time information to react quickly to changes and to gain a competitive advantage (Eisenhardt & Martin, 2000). Organizational performance in highly dynamic environments is linked to the capabilities of sensing and seizing opportunities, which involve differential access to existing information and scanning and interpreting activities to identify new opportunities (Teece, 2007).

The collection, analysis, and interpretation of digital data through suitable analytics enables effective differential access to existing customer information generated in real time and its strategic use (Chen et al., 2012; George, Haas, & Pentland, 2014; Watson, Wixom, Hoffer, Anderson-Lehman, & Reynolds, 2006).

Yet, how such information must be processed in decision-making activities is not specific, and two opposite and polarized standpoints exist in the literature.

On the one hand, a stream of management of information system and marketing studies has stated the importance of intensive customer data analysis to sense and seize opportunities. These studies claim that analytics positively affect organizational responsiveness and performance (see Germann, Lilien, & Rangaswamy, 2013; Roberts & Grover, 2012).

On the other hand, several management and marketing studies still support the effectiveness of a less analytical and more intuitive decision-making process (Agor, 1984; Elbanna, Child, & Dayan, 2013; Khatri & Ng, 2000; Persson & Ryals, 2014; Prietula & Simon, 1989; Rusetski, 2014).

This study seeks to contribute to the debate on analytical versus intuitive information processing by empirically verifying the hypothesis derived by both streams of the literature.

The empirical testing relies on 251 cases of the organizational deployment of both analytical customer information-processing activities based on mobile customer data analysis and intuitive activities that are more subject to a holistic and subjectivist interpretation of customer information.

The present paper aims to contribute to the previously mentioned debate and to the related literature in three ways.

First, this paper reviews and presents the main literature on the analytical versus intuitive information-processing debate, allowing us to draw a fundamental hypothesis on both theoretical stances. Second, most of the literature focuses mainly on the individual level of information processing without clarifying the impact at the organizational level. Instead, this study conceptualizes information processing at the organizational level and its impact on performance. Finally, no studies test these hypotheses in the context of real-time and location-sensitive data—issues that can affect the effectiveness of analytical customer information processing in terms of both speed and accuracy.

This article is structured as follows. Section 2 provides the theoretical framework for the study and outlines the hypotheses of the two polarized perspectives. Section 3 presents the data collection, methodology, and analyses. Section 4 presents the results, and Section 5 is devoted to discussion and conclusions.

### 3.2. Literature review and hypotheses

The debate over decision-making styles in organization and management fields dates back to the end of the 1970s and the 1980s (Agor, 1984; Kirton, 1976; Lusk, 1979; Prietula & Simon, 1989; Simon, 1987). However, even older contributions exist that introduced the main elements of the debate.

Chester Barnard, in *The Functions of the Executive* (1938), claimed that some decisions are made without an evident reasoning process, and the activity beyond the decision is “so unexplainable that we call it ‘intuition’” (Barnard, 1938, p. 305).

In the 1980s and 1990s, most authors in the fields of organization and management (see Table 3.1) were favorable to intuition as a way to cope with a highly dynamic environment characterized by incomplete information (e.g., Harper, 1988; McCarthy, Spital, & Lauenstein, 1987).

Intuition is viewed as a way to accelerate the decision-making process (Prietula & Simon, 1989) and to manage the trade-off between decision-making speed and accuracy (Khatri & Ng, 2000).

Another common issue is that executives and senior managers must use their intuition given the complexity and lack of complete information about problems at hand (Agor, 1984; Isenberg, 1984).

This debate over analytical versus intuitive information-processing styles was recently revitalized, particularly in the management and marketing literature related to organizational analytics tools (Erevelles, Fukawa, & Swayne, 2015; Persson & Ryals, 2014; Rusetski, 2014). In addition, the growth of digital data and information available to organizations has completely changed the previous informative scenario characterized by lack of data, and analytical tools exist to manage complex managerial issues (Chen et al., 2012; George et al., 2014; Van Knippenberg, Dahlander, Haas, & George, 2015).

[Table 3.1 here]

### *3.2.1 Analytical customer information processing: Mobile data and analytics*

One of the first contributions, which explicitly states the superiority of analytical and statistical information processing over intuitive processing, dates back to the 1950s and Meehl (1957). Additionally, at the end of the 1970s, when most contributions were favorable to intuitive information processing, some authors used empirical studies to support the concept that a highly analytical approach to decision making leads to higher task performance (Benbasat & Dexter, 1979; Lusk, 1979).

Interest in the deployment of an analytical information-processing style is growing fast in the contemporary context characterized by a “deluge of data” available to organizations (Day, 2011). An overabundance of customer data derives from the digitalization of marketing channels, the proliferation of digital media, and the fragmentation of customer touch points (Day, 2011). Decision making is now supported by the collection, storage, analysis, and visualization of extremely large, unstructured, and complex datasets (Chen et al., 2012; George et al., 2014; Xu, Frankwick, & Ramirez, 2015).

The availability of data generated and potentially analyzable in real time has set the stage for testing theoretical propositions based on the sensing and responding capabilities of the firm, especially in fast-changing environments (Teece, 2007; Teece, Pisano, & Shuen, 1997).

When the market is highly dynamic, firms can benefit from real-time information and, consequently, from real-time decision-making processes, thus achieving a competitive advantage (Eisenhardt & Martin, 2000; George et al., 2014; Ricciardi, Zardini, & Rossignoli, 2016). To do so, organizations must rely on data produced in real time, a feature that today characterizes the data produced in digital channels such as the Web, social media, and mobile devices (Fan & Gordon, 2014; George et al., 2014; Shankar, Venkatesh, Hofacker, & Naik, 2010). Moreover, real-time

data can be employed to gain insights useful for the customer decision-making process if organizations deploy analytical processes to make sense of the data and to use them strategically (Chen et al., 2012; Watson et al., 2006; Xu et al., 2015).

Indeed, the mobile device represents one of the most promising technologies in terms of real-time interactions between customers and organizations (Ghose et al., 2013; Shankar et al., 2010).

Different features characterize mobile devices when compared with other digital technologies. First, these devices are portable and permit individuals to ubiquitously access the Internet (Ghose et al., 2013; Shankar et al., 2016). This first characteristic also drives other, equally important, characteristics, such as searching for information from any location and permitting the retrieval of information on anything with a geographical proximity to the objects of interest (Ghose et al., 2013). Likewise, individuals can create and share user-generated content, such as comments on social media—once again, in proximity to the object—or the phenomenon involved in this interaction.

In this technological scenario, organizations can collect, analyze, and decide on how to interact with individuals in a geographically sensitive and real-time mode (Shankar et al., 2016).

However, “research on mobile BI [Business Intelligence] is still in an embryonic stage” (Chen et al., 2012, p. 1168) and the coming of Web 3.0—mainly location- and sensor-based—is creating significant opportunities for location-aware and person-centered analysis.

This latter recognition of a gap in research and the aforementioned features of mobile data are reasons why this study employs mobile data analytics processes as representations of highly analytical information processing.

The hypothesis development relies on the literature review (see Table 3.1), which upholds that the deployment of highly analytical information processing has a positive impact on responsiveness (i.e., Bhatt, Emdad, Roberts, & Grover, 2010; Davenport, 2006; Day, 2011) and organizational performance (i.e., Germann et al., 2014, 2013; Goll & Rasheed, 1997; McAfee & Brynjolfsson, 2012). Accordingly, this study develops the following hypotheses:

**H1.** Analytical information processing is positively related to organizational responsiveness.

**H2.** Analytical information processing is positively related to organizational performance.

In the literature favorable to intuition information processing, one of the main critiques of highly analytical decision making relates to the boundary condition of environmental dynamism. As it emerges from the literature review, severe limitations to the deployment of analytical information processing exist in turbulent, fast-changing, and uncertain environments, and intuition is considered more effective in such environments (Agor, 1984; Harper, 1988; Khatri & Ng, 2000; Prietula & Simon, 1989). In particular, the following criticisms are found: (1) the opportunity to collect all needed data given time constraints; (2) the doubtful disposability of necessary data; and (3) the information unreliability caused by the changing nature of environmental conditions (Khatri & Ng, 2000; Prietula & Simon, 1989). Nevertheless, in more recent developments of the organizational analytics literature, several authors emphasize the importance of deploying intense data and highly analytical information processing in fast-changing and dynamic environments (i.e., Bhatt et al., 2010; Day, 2011; Germann et al., 2013; Goll & Rasheed, 1997).

This stance is supported theoretically in the framework of Dynamic Capabilities (Eisenhardt & Martin, 2000; Teece, 2007). As Teece (2007) pointed out, analytical systems are fundamental elements of the “ecosystem framework for ‘sensing’ market and technological opportunities” (Teece, 2007, p. 1326).

In a highly dynamic and competitive environment, firms need a strong market and customer knowledge to sense new market trends (Bruni & Verona, 2009) and respond to changes in customer needs for new products or services (Barrett, Da-



vidson, & Vargo, 2015). Then, organizational analytical infrastructures and processes are important antecedents to support organizational sense and response capabilities in unpredictable and changing environments (Wang, Hu, & Hu, 2013).

Furthermore, also from an empirical point of view, the moderating effect of environmental dynamism in the relation between analytical information processing and organizational performance is partially verified (Germann et al., 2013; Goll & Rasheed, 1997). Then, this study develops the following hypotheses:

**H3.** Environmental dynamism positively moderates the relation between analytical information processing and organizational responsiveness.

**H4.** Environmental dynamism positively moderates the relation between analytical information processing and organizational performance.

### *3.2.2 Intuitive customer information processing: A holistic approach to customer data*

On the other side of the “fence,” several contributions exist that criticize analytical information processing or support intuitive processing.

The earliest evocation of the concept of “paralysis through analysis” (Peters & Waterman, 1982, p. 31) suggested that too much analysis slows down the decision-making process (Eisenhardt, 1990). Additionally, Prietula and Simon (1989) suggested that analytical information processing is attention- and time-consuming.

An intuitive decision-making style is considered the best way to cope with the speed of technological development, the complexity of managerial problems, and the incompleteness of the data and information needed to deploy analytical processes (Agor, 1984; Harper, 1988; McCarthy et al., 1987).

In a highly dynamic and unstable environment, certain constraints exist in using analytical and data-intensive decision-making processes: (1) time constraints; (2)

collection of a high volume of data to manage instability; (3) data reliability; and (4) data and knowledge incompleteness (Khatri & Ng, 2000).

Instead, intuition is characterized by “affectively charged judgments that arise through rapid, nonconscious, and holistic association” (Dane & Pratt, 2007, p. 33). The consequence of deploying intuition is the chance to quickly and effectively synthesize information (Dane & Pratt, 2007).

In the previous section, customer-related analytical information processing is delineated at an organizational level. Therefore, given the aim of this study, which is to compare customer-related analytical information and intuitive processing, a need exists to conceptually define the latter.

As Agor (1984) underlined, managers who deploy an intuitive decision-making process are more interested in solving problems by looking at the whole in a more informal and collegial manner. At the organizational level, inter-functional communication and meetings support the employment of an intuitive decision-making style (Agor, 1984). In addition, managers’ decision-making processes often rely on different informative sources, such as talking and relating to people inside the organization, and data come from different places and conversations (Khatri & Ng, 2000).

Often, organizations want to collect less quantitative and more subjective data, such as what a customer thinks about a firm’s products or reputation. To do so, they can rely on methods such as focus groups to elicit the communication of such information (Plax & Cecchi, 1989).

As Wibeck, Dahlgren, and Öberg (2007) underlined, intuition is central in discussions and focus groups to successfully facilitate the debate, to elicit information from customers, and to achieve a holistic view of an issue (Morgan, 1996; Plax & Cecchi, 1989; Wibeck et al., 2007). This is a fundamental trait of an intuitive information-processing approach (Isenberg, 1984; Khatri & Ng, 2000).

Intuition also plays a significant role in managers’ and staffs’ meetings and interactions, as Simon (1987) suggested: day-to-day manager–coworker interactions are loosely structured, intuitive, and qualitative (Simon, 1987).

Finally, the deployment of more qualitative information-gathering techniques that are not based on numerical data, such as focus groups and meetings, involves experience, judgment, and intuition (Wright & Geroy, 1991).

A theoretical conceptualization of intuitive information processing can be derived from seminal literature on customer information processing (see, i.e., Day, 1994; Glazer, 1991; Kohli & Jaworski, 1990).

Intuitive customer information processing can be conceptualized as a subset of the activities that characterize the customer knowledge process (Kohli & Jaworski, 1990; Li & Calantone, 1998), selecting activities that involve a high level of intuition, subjectivity, and a holistic approach. Then, intuitive customer information processing can be conceptualized as the process of acquiring, interpreting, and exploiting customer information inside the organization through activities such as marketing meetings and discussions, customer interviews and focus groups, and inter-functional meetings (Kohli & Jaworski, 1990; Li & Calantone, 1998).

The literature review (see Table 3.1) clearly presents both the theoretical and the empirical stances supporting the positive effects of deploying intuitive information processing.

The two main outcomes of intuition refer to different types of positive organizational performance (see, i.e., Agor, 1984; Cannella & Monroe, 1997; Dayan & Elbanna, 2011; Khatri & Ng, 2000) and to organizational responsiveness (Dane & Pratt, 2007; Eisenhardt, 1990; Prietula & Simon, 1989). Then, this study develops the following hypotheses:

**H5.** Intuitive information processing is positively related to organizational responsiveness.

**H6.** Intuitive information processing is positively related to organizational performance.

Another issue that often emerges in the reviewed literature regards the environmental conditions that influence the effectiveness of the two decision-making styles.

Fast-changing and turbulent environments are typically pointed to as the reasons why executives and managers should rely on intuition instead of on analytical processes (Agor, 1984; Eisenhardt, 1989; McCarthy et al., 1987). Technological changes are too rapid and extensive to obtain complete information about them and to deploy a full analytical plan; the CEO must rely on intuition and experience (McCarthy et al., 1987).

Furthermore, the positive moderating effect of environmental dynamism in the relation between intuitive information processing and organizational performance is empirically verified (Dayan & Elbanna, 2011; Khatri & Ng, 2000). In unstable environments, different constraints exist on data deployment, such as time constraints in collection, the need for large amounts to account for instability (Khatri & Ng, 2000), and sometimes the lack of “formulas” (Kleinmuntz, 1990) or quantitative data (Harper, 1988) for very complex managerial issues. Then, this study develops the following hypotheses on the moderation effect of environmental dynamism:

**H7.** Environmental dynamism positively moderates the relation between intuitive information processing and organizational responsiveness.

**H8.** Environmental dynamism positively moderates the relation between intuitive information processing and organizational performance.

### **3.3. Methods**

#### *3.3.1. Sample and data collection*

This study identified managers who have roles of responsibility in Marketing or related activities as potential respondents because they are most involved in and informed about customer information-processing activities.

The data for this research were obtained by employing a random sample from the AIDA-Bureau Van Dijk database, the most important database of all Italian limited companies.

The resulting frame was a sample of 1,200 potential respondents from a broad range of industries, geographical locations, and dimensions.

The respondents were assured of anonymity and the use of aggregated data to comply with Italian privacy law. A total of 251 responses were received, for a response rate of 20.9%. Of these, only 156 responses were fully completed and 95 were partially completed.

Organizational respondents represented a broad and equilibrated variety of industries: services (14%); information and telecommunications (13.6%); fashion and clothing (12%); manufacturing (8%); and food and beverage (6%). The firm sizes in the sample are measured following the EU Commission's size classes (2003/361/EC). Our sample displays 10.2% of micro firms with the number of employees between 0 and 9; 23.6% of small firms (10–49 employees); 29.6% of medium firms (50–249 employees); and 36.6% of large firms (>250 employees)

#### *3.3.2. Preliminary data analysis*

To decrease common method variance (CMV), this study followed best practices and procedural remedies (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) during the survey design and data collection phases.

The survey was pre-submitted to eight experts from both academia and business. They reviewed the survey items and helped develop the scale used to measure mobile analytics activities.

Other remedies followed were to assure respondents' anonymity and to avoid items' social desirability, demand characteristics, and ambiguity (Podsakoff et al., 2003).

Once data were collected, common method bias was tested employing Harman's single-factor test (Podsakoff et al., 2003; Woszczynski & Whitman, 2004).

The variance explained by the one factor in the unrotated factor matrix is 27.9%, largely lower than the suggested 50% threshold. This result indicates that common method bias is not a significant problem in this study.

To check for non-response bias, the different groups of early and late respondents were tested with ANOVA. No significant differences were found between the two groups, indicating that non-response bias is not a major concern for this study.

Regarding missing data, a preliminary analysis using Little's MCAR test indicated a missing completely at random (MCAR) mechanism ( $\chi^2(83) = 75.47, p = .71$ ). Given the missing MCAR mechanism, this study applied listwise deletion as treatment for missing data, which is considered unbiased under the MCAR condition (Newman, 2014).

### *3.3.3. Measures*

Table 3.2 lists the presented items, Cronbach's alpha scores, and factor loadings of each construct. In the preliminary data analysis, an exploratory factor analysis (EFA) with principal axis factoring and oblique rotation was employed to verify the new scale (analytical information processing) and the general items' loadings. All factor loadings are higher than 0.5, suggesting adequate item reliability.

To further explore the validity and reliability of the model employed, a CFA analysis shows adequate results: CFI = .97, TLI = .96, RMSEA = .05, and SRMR = .06.

For each construct, the average variance extracted (AVE) is greater than the squared correlation coefficient of the respective paired constructs (see Table 3.3), providing support for discriminant validity (Fornell & Larcker, 1981).

*Analytical Customer Information-processing (ACIP)*: This scale is developed to measure the organizational-level activities of customer-related analytical information processing based on mobile technologies. Starting from the literature review, items are developed on mobile technologies and six expert interviews. The items, tested using exploratory EFA, demonstrate consistent loading on one factor, and the only item showing a low loading is the reverse item.

*Control variables*: Firm sizes are measured using seven ranges of numbers of employees, based partially on the EU SME classification.

Additionally, business longevity is considered by employing the common log of business age. To control for industry, three dummy variables are introduced to account for the most represented industries (ICT, services, and fashion).

[Table 3.2 here]

[Table 3.3 here]

### **3.4. Results**

The results of multiple regression and multiple moderated regression are presented in Table 3.4. The moderator variable used is Environmental Dynamism (ED) and the variable is centered to reduce multicollinearity before computing the different interaction terms (Aiken & West, 1991). Model 1 to Model 4 are employed to test the hypothesis involving customer responsiveness (CR), and then Model 5 to Model 8 use market performance (MP) as a dependent variable.

Models 1 and 5 consider control variables only; Models 2 and 6 present the multiple

regression with independent variables and a moderator; Models 3 and 7 also consider the interaction terms between independent variables and a moderator; lastly, Models 4 and 8 present parsimonious models without considering control variables. Hypotheses 1 and 2 claim that analytical customer-related information processing (ACIP) is positively related to both the outcomes MP and CR, but all models suggest no significant correlation between them.

Instead, the relationships between intuitive customer-related information processing (ICIP) and both CR ( $B = .33, p < .001$ ) and MP ( $B = .26, p < .05$ ) are positive and significant; this evidence confirms Hypotheses 5 and 6.

Then Models 3, 4, 7, and 8 are employed to verify the hypothesis concerning the ED role as a moderator in the relationship between dependent variables and both outcomes.

Hypotheses 7 and 8, which claim a positive moderation effect of ED in the relationships between ICIP and both outcomes, have no empirical support. The interaction term ICIP x ED is not significant in all models.

One of the most interesting pieces of evidence regards Hypotheses 3 and 4. Models 3, 4, and 7 show that the interaction term ACIP x ED is positive and significant ( $p < .05$ ), which supports Hypotheses 3 and 4.

To further explore this evidence, this study employed the SPSS computational procedure PROCESS (Hayes, 2013), which allows for slope analysis at three moderator levels (high, moderate, and low). The analysis supports the presence of a moderation effect of ED in the relationship between ACIP and CR ( $B = .12, p < .001$ ). In addition, the slope analysis in Figure 1 shows that the slope changes sign, passing from low to high levels of ED, which supports Hypothesis 3. The same analysis with MP as outcomes gives partial support to Hypothesis 4. In fact, for low and moderate ED ( $-1SD$  and mean), the bootstrapped confidence intervals contain zero and are not significant. With high levels of ED ( $+1SD = 1.14$ ), the effect is significant and the bootstrapped confidence interval does not contain zero ( $B = .18, p < .05, LLCI = .01, ULCI = .35$ ).

[Figure 3.1 here]



### **3.5. Discussion and conclusion**

#### *3.5.1 Theoretical implications*

Theoretically, this study contributes to both the management and the IS literature, reframing the long-standing debate about analytical versus intuitive information processing in the actual context of mobile technologies. The mobile context has changed the organizational information-processing scenario, especially as a result of the real-time and location-sensitive nature of customer data. These data are not suitable for processing with intuitive activities given their quantity and complexity, and then they do not conceptually overlap with other types of customer data that are still processed using intuitive information processing. This issue permits the disentanglement of the two processes at the organizational level, allowing their relationships to be theoretically hypothesized with organizational responsiveness and performance.

By employing a large-scale survey, this study finds evidence that reconciles the two polarized theoretical stances. The external ED level works as a moderator in the relationship between analytical customer information processing and outcomes. At a high ED level, analytical approaches are positively related to both customer responsiveness and market performance. At moderate and low ED levels, this construct is not significant. Only intuitive customer-related information processing displays positive relationships with outcomes.

In some sense, this evidence confirms Simon's claim: "The effective manager does not have the luxury of choosing between 'analytic' and 'intuitive' approaches to problems" (Simon, 1987, p. 63).

### *3.5.2 Managerial implications*

Two main managerial implications can be derived from this study. First, managers must be aware of the importance of intuitive customer information processing that enhances related organizational-level activities. Even in an actual data-rich context, a holistic and intuitive approach to customer knowledge and decision making still plays the most significant role in organizational responsiveness and performance.

Then, managers who operate in highly dynamic and turbulent environments must also rely on analytical information processing, especially when customers' real-time data are available.

### *3.5.3 Limitations and future research*

Despite its contributions, this study is constrained by some limitations. First, employing self-reported perceptual data based on a single key informant could weaken the study's internal validity. Even if substantial precautions are taken to narrow common method variance, future research should provide a sampling of multiple respondents for each organization to check for inter-rater validity.

Second, customer-related analytical information processing is framed only in the mobile technologies context. Mobile data, as previously noted, have specific features, such as a real-time and location-sensitive nature, that enhances their value in the customer decision-making process. To enhance the generalizability of the empirical findings of this study, future research should address other types of customer data, such as user-generated content on social media, and other information processing subjects, such as technological developments and competitors, for both analytical and intuitive information-processing activities.

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## Tables and figures

**Table 3.1.** Literature review

Authors (years)	Information processing	Environmental conditions	Outcomes
Agor (1984)	Intuitive	Turbulent, rapid changes, complexity.	(+) Effective decision making in different functions (i.e., HR, Marketing...)
McCarthy, Spital, & Lauenstein (1987)	Intuitive (“gut feel”)	Fast-moving, high technology, uncertainty.	(+) Positive impact on technological developments decision making.
Harper (1988)	Intuitive	Lack of information, fast changing, uncertainty.	(+) Size new opportunities.
Prietula & Simon (1989)	Intuitive	Not defined.	(+) Speed up responsiveness, need less informative effort.
Eisenhardt (1990)	Intuitive	Fast-moving, high technology.	(+) Speed up responsiveness.
Cannella & Monroe (1997)	Intuitive	High level of ambiguity.	(+) Innovation outcomes.
Andersen (2000)	Intuitive	Not defined.	(+) Organizational effectiveness.
Khatri & Ng (2000)	Intuitive	Unstable.	(+) Positive impact over performance.
Khatri & Ng (2000)	Intuitive	Stable.	(-) Negative impact over performance.
Covin, Slevin, & Heeley (2001)	Intuitive	High technology. Changes in technological standards.	(+) Organizational performance.
Hayashi (2001)	Intuitive	Complex, ambiguous, turbulent.	(+) Effective strategic decision making.
Dane & Pratt (2007)	Intuitive	Environmental uncertainty.	(+) Fast and accurate decision making.
Dayan & Elbanna (2011)	Intuitive	Environmental turbulence.	(+) Market success of new product. Speed to market.
Elbanna, Child, & Dayan (2013)	Intuitive	Environmental turbulence, instability, hostility.	(+) Organizational performance. (not empirically confirmed)
Matzler, Uzelac, & Bauer (2014)	Intuitive	Not defined.	(+) Organizational innovativeness.
Huang & Pearce (2015)	Prevalent intuitive (+ formal analysis)	Extreme uncertainty.	(+) Positive correlation with new venture success.
Lusk (1979)	Analytical	Not defined.	(+) Higher task performance.
Benbasat & Dexter (1979)	Analytical	Not defined.	(+) Higher profitability and faster decision making.

Prietula & Simon (1989)	Analytical	Not defined.	(+/-) Support the intuitive process, but consumes attention and time.
Eisenhardt (1990)	Analytical (forecasting)	Fast-moving, high technology.	(-) Slow down responsiveness.
Goll & Rasheed (1997)	Analytical	Highly dynamic and highly munificent environment.	(+) Organizational performance.
Covin, Slevin, & Heeley (2001)	Analytical	Low technology. Predictable environment.	(+) Organizational performance.
Davenport (2006)	Analytical (deployment of analytics)	Not defined.	(+) Organizational performance and responsiveness.
Bhatt, Emdad, Roberts, & Grover (2010)	Analytical (information leveraging)	Dynamic environment.	(+) Organizational responsiveness.
Trkman, McCormack, De Oliveira, & Ladeira (2010)	Analytical (deployment of analytics)	Changing environment.	(+) Supply chain performance.
Day (2011)	Analytical (quasi-experiment with digital data)	Accelerating complexity, fragmentation, rapid changes.	(+) Organizational responsiveness and adaptation.
Barton & Court (2012)	Analytical	Not defined.	(+) Competitive advantage.
McAfee & Brynjolfsson (2012)	Analytical (data-driven decision making)	Not defined.	(+) Higher productivity and profitability.
Germann, Lilien, & Rangaswamy (2013)	Analytical (deployment of analytics)	Hyper-competitive and fast-changing environment.	(+) Organizational performance.
Germann, Lilien, Fiedler, & Kraus (2014)	Analytical (deployment of analytics)	Not defined.	(+) Organizational performance.
Erevelles, Fukawa, & Swayne (2015)	Analytical (employing Big Data analytics)	Hyper-competitive environment.	(+) Sustainable competitive advantage.

**Table 3.2.** Construct, Cronbach's alpha scores, items, and factor loadings

Construct	Items #	Scale items and factor loadings	Source
Analytical Customer Information-processing ( $\alpha = .84$ )	ACIP 1	We habitually use mobile analytics tools to collect information about customer. (0.89)	Developed for this study
	ACIP 2	Data from mobile analytics are crucial in supporting customer-related activities. (0.90)	
	ACIP 3	We rarely employ data from mobile analytics to support forecasting about customers' needs and preferences. (0.59) (R)	
	ACIP 4	Decision making about customers is supported using mobile analytics data. (0.88)	
Intuitive Customer Information-processing ( $\alpha = .67$ )	ICIP 1	We regularly meet customers to learn their current and potential needs for new products. (0.75)	Adapted from Jayachandran et al. (2004), Li and Calantone (1998)
	ICIP 2	We have interdepartmental meetings regularly to discuss customers' needs. (0.65)	
	ICIP 3	Marketing personnel in our business unit spend time discussing customers' future needs with other functional departments. (0.74)	
Environmental Dynamism ( $\alpha = .83$ )	EV 1	We are witnessing demand for our products and services from customers who never bought them before. (0.72)	Adapted from Jayachandran et al. (2005)
	EV 2	The technology in our industry is changing rapidly. (0.82)	
	EV 3	Technological changes provide big opportunities in our industry. (0.82)	
	EV 4	A large number of new product ideas have been made possible through technological breakthroughs in our industry. (0.86)	
Customer Responsiveness ( $\alpha = .89$ )	CR 1	We respond rapidly if something important happens with regard to our customers. (0.79)	Adapted from Homburg et al. (2007)
	CR 2	We quickly implement our planned activities with regard to customers. (0.89)	
	CR 3	If our customer-related activities do not lead to the desired effects, we are fast at changing them. (0.80)	
	CR 4	We quickly react to fundamental changes with regard to our customers. (0.86)	
Market performance ( $\alpha = .94$ )		In the last three years, relative to your competitors, how has your business unit performed with respect to:	Homburg et al. (2007)
	MP 1	Achieving the desired profit and revenue level?* (0.92)	
	MP 2	Achieving the desired growth?* (0.96)	
	MP 3	Achieving/securing the desired market share?* (0.94)	

\* Seven-points rating scale anchored by "clearly worse" [1], "competition level" [4], and "clearly better" [7]

**Table 3.3.** Means, standard deviations, inter-construct correlations, and discriminant validity

Constructs	Mean	S.D.	AVE	1	2	3	4	5
1. Analytical Customer Information-processing	4.13	1.64	.62	1				
2. Intuitive Customer Information-processing	5.15	1.13	.43	.26	1			
3. Environmental Dynamism	5.01	1.14	.58	.38	.27	1		
4. Customer Responsiveness	5.80	.97	.65	.18	.44	<u>.06</u>	1	
5. Market Performance	4.85	1.22	.83	.20	.29	.22	.26	1

AVE = average variance extracted; SD = standard deviation.

The underlined correlation is not significant; all the other correlations are significant at  $\alpha = .05$  (two-tailed)

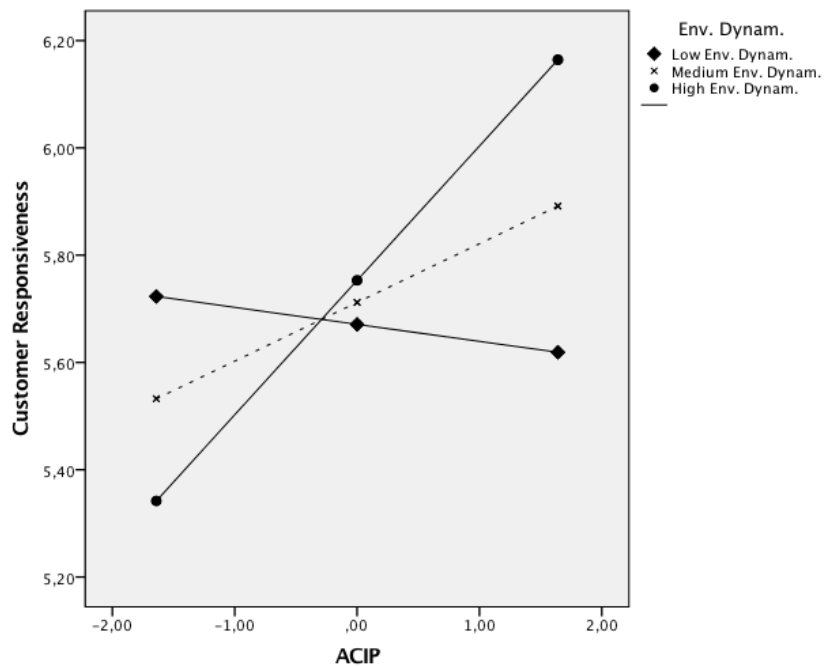
**Table 3.4.** Regression results on customer responsiveness and market performance

	Model 1 Customer Re- sponsiveness B (s.e.)	Model 2 Customer Re- sponsiveness B (s.e.)	Model 3 Customer Re- sponsiveness B (s.e.)	Model 4 Customer Re- sponsiveness B (s.e.)
<i>Controls</i>				
Constant	5.54 (.31)***	4.07 (.47)***	3.86 (.47)***	3.75 (.39)***
Number of employees (7 ranges)	-.15 (.05)**	-.12 (.05)*	-.12 (.05)*	
Log of business age	.43 (.21)*	.32 (.19) <sup>+</sup>	.31 (.19)	
ICT	.49 (.26) <sup>+</sup>	.42 (.25) <sup>+</sup>	.36 (.25)	
Fashion	.24 (.25)	.17 (.23)	.21 (.22)	
Services	.62 (.24)**	.43 (.22) <sup>+</sup>	.34 (.23)	
<i>Independent variables</i>				
ACIP		.05 (.05)	.06 (.05)	.06 (.05)
ICIP		.33 (.07)***	.33 (.07)***	.37 (.06)***
<i>Moderator variable</i>				
ED		-.07 (.07)	-.04 (.07)	-.04 (.07)
<i>Interaction terms</i>				
ACIP x ED			.09 (.04)*	.12 (.04)**
ICIP x ED			-.002 (.06)	.002 (.06)
F	4.16**	6.63***	6.06***	10.72***
Adjusted R <sup>2</sup>	.09	.22	.25	.24
df	5	8	10	5

	Model 5 Market Performance B (s.e.)	Model 6 Market Performance B (s.e.)	Model 7 Market Performance B (s.e.)	Model 8 Market Performance B (s.e.)
<i>Controls</i>				
Constant	4.61 (.40)***	2.36 (.65)***	2.10 (.69)**	2.54 (.54)***
Number of employees (7 ranges)	-.06 (.07)	-.07 (.07)	-.07 (.07)	
Log of business age	.32 (.27)	.32 (.27)	.31 (.27)	
ICT	.002 (.35)	-.20 (.35)	-.28 (.34)	
Fashion	-.04 (.32)	-.32 (.31)	-.43 (.31)	
Services	-.08 (.32)	-.18 (.32)	-.13 (.31)	
<i>Independent variables</i>				
ACIP		.09 (.07)	.10 (.07)	.07 (.06)
ICIP		.26 (.09)**	.26 (.09)**	.26 (.09)**
<i>Moderator variable</i>				
ED		.13 (.09)	.16 (.09) <sup>+</sup>	.13 (.09)
<i>Interaction terms</i>				
ACIP x ED			.11 (.05)*	.09 (.05) <sup>+</sup>
ICIP x ED			.001 (.08)	-.02 (.08)
F	.35	2.88**	2,749**	4.34**
Adjusted R <sup>2</sup>	-	.09	.10	.10
df	5	8	10	5

<sup>+</sup>  $p < .1$   
<sup>\*</sup>  $p < .05$   
<sup>\*\*</sup>  $p < .01$   
<sup>\*\*\*</sup>  $p < .001$

**Figure 3.1.** Hypothesis 3 Interactions Term Plot for Customer Responsiveness



## **PAPER 4**

### **Social Media and Organizations' Technological Opportunism: Social Media Analytics as a Source of Technology-Related Information**

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#### **Abstract**

In the last decade Social Media (SM) have evolved from being an interesting technology only for corporate communication and public relations toward a proper business tool. Then recent studies have addressed the role SM in creating value for organizations. One of the most contemporary stream of literature has investigated the impact of SM, as sources of information and knowledge, on innovation outcomes. The results suggest that SM have negative effects when considered a source of technology-related or solutions' information. This study addresses the issue investigating the role of SM analytics, as tools and activities to make sense of SM data, in supporting Technological Opportunism (TO), defined as the organizational capability of sensing and responding to technological changes. The findings show that Technological Opportunism (TO) is supported by SM analytics. The research model also highlights which are the constructs that significantly act as antecedents of SM analytics deployment.

**Keywords:** social media – technological opportunism – analytics – organizational performance

#### 4.1. Introduction

The centrality of Social Media (SM) in business and organizational debate is a matter of fact. To cite the most important evidence, active SM users worldwide reached, in 2016, the unthinkable number of 2.31 billion; almost a third of the population of the world; an increase of 216 million compared to 2015 (Kemp, 2016).

Investment in SM activities has rapidly increased, functions dedicated to SM management within companies has consistently growth, confirming the willingness of organizations to employ SM to enhance performance (Roberts & Piller, 2016). Despite this rapid growth in managerial interest in SM as a tool for business, its employment in one of the most promising areas, innovation, is still lagging behind (He & Wang, 2015; Roberts, Piller, & Lu, 2016).

When academic research about SM began, the main focus was on the radical changes that SM had brought to corporate communications, public relations, and organization-customer interactions (Kaplan & Haenlein, 2010; Kietzmann, Hermkens, McCarthy, & Silvestre, 2011). In the years following, organizations started to deploy SM as a tool to support both overall business activities, such as marketing and customer relationship management (He & Wang, 2015; Trainor, Andzulis, Rapp, & Agnihotri, 2014), and also very specific activities, such as understanding customers' sentiments and emotions, and online brand communities behavior (Fan & Yan, 2015). Also, from an empirical point of view, SM academic research has started to investigate the relationship between the deployment of SM and business performance.

Paniagua and Sapena (2014) found a direct, and positive, relationship between the numbers of followers on corporate SM, and firms' stock prices, clearly postulating the argument that social media resources can be transformed into business performance capabilities (Paniagua & Sapena, 2014). The impact of SM on business-to-business sales performance has also been analyzed and shows a positive impact on the creation of new opportunities, the relationships management, and the improvement of sales performance (Rodriguez, Peterson, & Krishnan, 2012).

Despite managerial awareness of SM centrality in connecting, interacting, and collaborating with customers, recent managerial literature has called for more research on the SM relationship with innovation (Mount & Martinez, 2014).

The central issue is the presence, inside the different SM channels, of huge amounts of customers' information that can be employed in the whole innovation funnel phases: idea creation, R&D, and commercialization (Mount & Martinez, 2014).

Social media has the: "potential to harness diverse knowledge and foster innovation among a wider network of users and partners." (Du, Yalcinkaya, & Bstieler, 2016, p. 56).

Therefore, in very recent years, some theoretical and empirical studies have addressed the SM relationship with innovation outcomes, in particular with New Product Development (NPD) (see i.e. Carr et al., 2015; He & Wang, 2015; Roberts et al., 2016). What emerges is that SM have a positive and significant relationship with NPD outcomes (Roberts & Piller, 2016).

Given the very recent interest academic research has shown towards the issue of the SM role within innovation processes, the literature is scarce, and remarkable gaps are still present. In particular, no research has yet addressed the role of SM in enhancing organizational sensing and responding capabilities with regards to technological changes, which are the antecedents of organizational radical innovation adoption (Srinivasan, Lilien, & Rangaswamy, 2002). In the actual context of a highly dynamic market, characterized by fast changes in both customer needs and technological innovation (Teece, 2007), organizational capabilities of sensing and responding to external changes are a central issue. The risk of not sensing technological developments and changes, is to lose sustainable competitive advantage accrued over years of market success.

There are several examples of successful firms that have lost their competitive positions because of their inability to sense important technological shifts. To give just two well-known examples: there was the Kodak failure to pursue the digital revolution in photography (Lucas & Goh, 2009), and Nokia's inability to first understand the market's preference for clamshell phones in 2004 (Bhutto, 2005), and then the company's defeat in the: "smartphone battle" (Vuori & Huy, 2015).



Contemporary organizations need the capability of sensing and responding to technological developments and changes (Srinivasan et al., 2002), also known as Technological Opportunism (TO).

Another gap should be linked to the choice of measuring directly the SM technology without taking into consideration that SM data are complex, informal and episodic (He & Wang, 2015). This study addresses the previous gap measuring the organizational level of SM analytics deployment intended as the technologies, systems and practices that permit to make sense of SM data at organizational level.

Moreover SM analytics practices rely on organizational cross-functional projects, which typically involved Marketing and IT (Fan & Yan, 2015), and on individual digital analytics skills, which are becoming fundamental due to the skills gap created by the digital era (Leeflang, Verhoef, Dahlström, & Freundt, 2014). Then we also investigate the two previous-mentioned issues in the research model in order to account also for the antecedents of SM analytics deployment.

This study aims to contribute to the existing debate in several ways. First it wants to contribute to SM literature, reframing the role of SM inside the TO theoretical framework. Then it empirically verifies the role of SM analytics deployment as antecedent of TO. It also contributes to TO literature by verifying the importance of cross-functional integration of Marketing and IT functions in order to enhance organizational TO.

## **4.2. Theoretical framework and hypotheses development**

### *4.2.1. From technology orientation to technological opportunism*

The central role of technological changes in strategy development dates back to the '70 with Nyström (1979) study on technology-oriented firms.

The firms able to search within their respective technology areas for product ideas, based on new technical principles, display higher level of innovativeness if compared to more market-oriented firms (Nyström, 1979).

In table 4.1 it is presented the evolution of the theoretical conceptualization of firms' ability to cope with technological changes in management literature.

This evolution of the literature can be basically divided in two main period splitted by the contribution of Srinivasan, Lilien & Rangaswamy (2002) that acts as border line between the two.

On one hand, in the first period, the main conceptualization can be labeled as “technological orientation” (sometimes also R&D orientation). This first concept refers to firms' “orientation and commitment to new product program” (R. G. Cooper, 1984, p. 254) and their “ability and will to acquire a substantial technological background and use it in the development of new product” (Gatignon & Xuereb, 1997, p. 78)

The technological orientation mainly refers to the “capability of the organization to develop new technologies, products, and processes” (Srinivasan et al., 2002, p. 49), in this sense it follows the Resource Based View (RBV) considering technologic orientation as a complex bundle of resources and capabilities (Barney, 1991; Wernerfelt, 1984) able to sustain new technology development inside the firms.

On the other hand from the contribution of Srinivasan, Lilien & Rangaswamy (2002) the foundational theoretical framework the conceptualization of firms' ability to cope with technological changes, shifts towards the Dynamic Capabilities (DC) perspective (Teece, Pisano, & Shuen, 1997).

Rooted in DCs' theoretical framework Technological Opportunism (TO) is defined as a “sense-and-respond capability of firms with respect to new technologies” (Srinivasan et al., 2002, p. 48). Then the authors explicitly identified the two distinct components that characterize TO; (1) the technology-sensing capability or the “organization's ability to acquire knowledge about and understand new technology developments, which may be developed either internally or externally”; and (2) the

technology-response capability or the “organization's willingness and ability to respond to the new technologies it senses in its environment that may affect the organization” (Srinivasan et al., 2002, pp. 48–49).

This conceptualization anticipates the more general DCs microfundation framework (Teece, 2007) in which the author defines all the processes that undergird DCs, grouped in three macro-categories of sensing, seizing and transforming capabilities.

From the Srinivasan, Lilien & Rangaswamy (2002) paper, the following studies on TO tend to converge over their definition of TO with minor integrations or modifications (see Table 4.1).

What significantly changes in the following developments of the literature are the hypotheses about the possible organizational outcomes generated by TO.

In the early contributions the main focus is on studying the relationship between TO and new technology adoption (Garrison, 2009; Srinivasan et al., 2002). Then in more recent study also the positive effect of TO over organizational performance is taken into consideration (Chen & Lien, 2013; Sarkees, 2011).

A fundamental microfundation of DC, which leads to sensing and seizing external opportunities achieving sustainable competitive advantage, resides in organizations capacity of “interpreting available information in whatever form it appears”, not least the “news of scientific and technological breakthroughs” (Teece, 2007, p. 1323). Firms need to deploy the necessary activities for “scanning and monitoring internal and external technological developments” in order to develop the organizational processes “to garner new technical information [...] and shape new products and processes opportunities” (Teece, 2007, p. 1323).

Following the previous TO literature (Chen & Lien, 2013; Lucia-Palacios, Bordonaba-Juste, Polo-Redondo, & Grünhagen, 2014; Sarkees, 2011) and the theoretical microfundation of DCs (Teece, 2007) this study comes to the following hypothesis:

**H1.** There is a positive relationship between the degree of Technological Opportunism and firm performance.

[Table 4.1 here]

#### *4.2.2. The role of Social Media in enhancing organizational technological opportunism*

As said in the introduction at the beginning of the academic research on SM the main focus was mainly on the radical changes that SM were bringing to corporate communications, public relations, and organization-customer interactions (Kaplan & Haenlein, 2010; Kietzmann et al., 2011).

The idea that the information available on SM channels can be employed in innovation process is extremely recent (Mount & Martinez, 2014). Recent studies have investigated the role and the importance of SM in relation with organizational innovation (He & Wang, 2015; Jalonen, 2015; Roberts et al., 2016).

SM technologies “constitutes a widely used and powerful means of inbound open innovation activities, enabling a firm to effectively acquire and leverage external knowledge” (Du et al., 2016, p. 56)

The SM channel potentially can bring several positive outcomes to organizations able to exploit their informative potential, such as: (1) creativity, which can emerge from “network interactions across of a mass of users with diverse knowledge”; (2) expertise, derived from the activities of “environmental scanning” and the “identification of merging trends”; and (3) collective intelligence, because the “access to a diverse range of skills, capabilities, and knowledge allows participants to blend disparate solutions in new and novel ways” (Mount & Martinez, 2014, p. 126).

Then SM can be employed to better understand customer needs, as well as keeping abreast of new technical knowledge, and solutions’ information (Roberts et al., 2016).

But the positive effect of SM, as source of solutions' information, on innovation outcomes is not straightforward (Roberts et al., 2016), because SM is, "primarily complex, informal and episodic" (He & Wang, 2015, p. 263) and available data is often, "qualitative and highly unstructured" (Chan, Wang, Lacka, & Zhang, 2016). If the right analytics and skills are not employed to make sense of the data (e.g. Chen et al., 2012; Davenport, 2006; LeeFlang et al., 2014), then the effect of SM as a tool could be counterproductive in respect of NPD outcomes (Roberts et al., 2016).

To shed some light on the above-mentioned issue, this study conceptualizes and operationalizes the theoretical construct of "Social Media analytics deployment", in order to verify if it exists a positive relationship between SM analytics activities and organizational TO. The main idea is that given the complex, informal, and episodic nature of social media data, information must be filtered and managers have to be capable of making sense of them (Teece, 2007). Indeed one of the main characteristic of a technological opportunistic firm is the: "regularly scan for information about the development of new technologies that are viewed as potential sources of growth" (Chen & Lien, 2013, p. 2219). But these technology-related information need to be gathered and filtered in order to make sense of them and understanding implication for action (Teece, 2007).

This study conceptualizes social media analytics deployment as the technologies, systems and practices that permit to make sense of social media data to help the firm to better understand external environment and make timely decisions (Chen et al., 2012; Fan & Gordon, 2014; Fan & Yan, 2015). Following this argumentation this study hypothesizes:

**H2.** There is a positive relationship between the degree of Social Media analytics deployment and organizational technological opportunism.

#### *4.2.3. The role of inter-functional integration in supporting SM analytics deployment and skills*

One of the most common cause of failure of project involving Marketing and IT functions is linked with the divergent goals and backgrounds of the two functions involved (Cooper, Gwin, & Wakefield, 2008). To solve the previous-mentioned issue and obtain firm performance from IT-related project, there is the need of integration IT function with other functional areas and departments of the the firm (Cooper et al., 2008; Wade & Hulland, 2004).

Given the cross-functional nature of SM analytics activities, which, at least, involves Marketing and IT functions, there is the need for strong cross-functional integration to support SM new technology adoption and deployment (Kim & Pae, 2007), and to ensure sharing of the specific knowledge characterizing each separate unit (Tsai, 2002). As previously introduced firm's sensing capabilities are, in general, positively supported by the scanning and filtering of relevant information about external changes and opportunities (Teece, 2007). These activities are under the responsibility of both the IT department, for the technical and information systems parts, and the Marketing function that can develop, "conjecture or a hypothesis about the likely evolution of technologies, customer needs, and marketplace responses" (Teece, 2007, p. 1323). Therefore Marketing and IT integration can also directly enhance an organization's sensing-and- responding capabilities as they relate to new technology developments. Given these argumentations the following hypotheses are developed:

**H3.** There is is a positive relationship between the degree of Marketing/IT integration and Social Media analytics deployment.

**H4.** There is is a positive relationship between the degree of Marketing/IT integration and organizational technological opportunism.

Another central issue linked to Marketing and IT inter-functional integration is the skills gap related to the digitalization of marketing channels and firm-consumer interactions (Yadav & Pavlou, 2014)

This phenomenon is widening the organizational skills gap in terms of expertise in social networking, deep customer analytics, and digital media (Day, 2011), causing a, “talent gap” in all the activities related to the digitalization of organization-customer interactions (Leeflang et al., 2014). The relevant knowledge to address this challenge is dispersed in different organizational, “silos” (Day, 2011), such as Marketing and IT functions, and only cross-functional dialogue and learning can enhance the development of “deep expertise in next-generation marketing capabilities” (Day, 2011, p. 184).

Moreover, as said before, SM data are complex and unstructured (Chan et al., 2016), then to make sense of those data is necessary to employ digital analytical tools and activities in order to understand and respond to technological changes. These tools and activities are quite novel and require specific skills and knowledge (Westerman, Tannou, Bonnet, Ferraris, & McAfee, 2012) in order to support related analytics deployment (Germann, Lilien, & Rangaswamy, 2013). Following these argumentations this study hypothesizes:

**H5.** There is a positive relationship between the degree of Marketing/IT integration and the level of digital analytics skills.

**H6.** There is a positive relationship between the degree of Marketing/IT integration and Social Media analytics deployment.

Following the previously introduced theoretical framework, all the developed hypotheses are presented in the research model in Figure 1.

[Figure 4.1. here]

### **4.3. Research methodology**

#### *4.3.1. Sample and data collection*

In order to test the research model, a survey has been developed employing both constructs already present in TO literature, and a new scale for measuring the SM analytics deployment in a technology sensing-and-responding context (see Table 4.2). The survey is developed, pre-tested and refined in collaboration with eight experts, four from academia, and four from a consultancy and business environment. A first pre-test of the survey was conducted with a sample of 30 firms.

The target respondents' firms for this research were obtained from a state-of-the-art commercial database of all the limited Italian companies (AIDA – Bureau Van Dijk).

Managers with roles of responsibility in Marketing or related activities are identified, as potential respondents, because of their engagement in new product and solutions' information scanning and filtering activities. Moreover they are most involved in, and informed about, activities related to sensing and responding activities (Roberts & Grover, 2012). The sample of potential respondents consists in a list of 1200 firms across a wide spectrum of different industries, geographical locations, and dimensions.

To comply with privacy laws anonymity and aggregate use of data were assured to respondents. Then in order to increase the response rate, the authors offered to provide them with a study results' report, and also it is extended an invitation to attend a workshop related to the study, as incentives to participate. The responses were collected in approximately twelve weeks.

A total of 251 responses were received, which represents a response rate of 20.9%. Of the 251 questionnaires received, 156 were fully completed, and 96 were partially completed; in this latter case missing data treatments were employed to partially recover the information from incomplete surveys.



Organizational key informants represented a wide and equilibrated variety of industries: Services (14%); ICT (13.6%); fashion and clothing (12%); manufacturing (8%); food and beverage (6%). Other industries were also represented with a cumulative percentage of less than 6% (e.g. pharmaceutical, bank and assurance, automotive, chemical, electronics...). In terms of business size, the sample displays the following distribution: a 10.2% of micro firms with a number of employees between 0 and 9; a 23.6% of small firms (10-49 employees); 29.6% of medium firms (50-249 employees); and 36.6% of large firms (>250 employees).

#### *4.3.2. Variable definition and measurement*

*Social Media analytics deployment*: this construct measure the level of deployment of Social Media analytics inside organizational processes and decision-making related to technological developments and changes. In order to develop this scale, the study follows an approach similar to the construction of technology-use index (Jayachandran, Sharma, Kaufman, & Raman, 2005; Trainor et al., 2014) and analytics deployment multi-items construct (Germann et al., 2013). Also this measurement scale was developed and refined in collaboration with the previously mentioned eight experts and pre-tested with the sample of 30 respondents.

*Marketing and IT integration*: measures the level of integration between the two functions in activities related to cross-functional projects (e.g. CRM, SM Analytics), setting project priorities and generate new project ideas in close collaboration (Cooper et al., 2008; Peltier, Zahay, & Lehmann, 2013).

*Digital analytics skills*: given the importance of digital-related skills in supporting the new scenario of digitalization (Leeflang et al., 2014), especially in the analytics activities (Day, 2011; Royle & Laing, 2014) this construct measure the level of Social Media analytics skills of the personnel adapting a previous measurement scale related to customer analytics skills (Germann et al., 2013).

*Technological opportunism*: in order to measure the level of organizational TO this study employs three items to measure technology-sensing capabilities, and four to

measure technology-reponse capability. The first three items are adapted directly from Srinivasan et al. (2002). Instead the items related to responding capability are slightly modified due to the eight expert advices. Then two items are directly from Srinivasan et al. (2002) and the other two are adapted from the organizational responsiveness framework developed in Homburg et al. (2007), to further reinforce the responsiveness side of TO theoretical construct, which is a bit unclear in the other two items in the seminal study (Srinivasan et al., 2002).

*Firm performance:* in order to test the relationship of TO with firm performance, this study follows previous approaches (Chen & Lien, 2013) measuring both market and financial-related performance adapting a widely employed measurement scale (Homburg, Grozdanovic, & Klarmann, 2007).

[Table 4.2 here]

#### 4.3.3. Preliminary data analysis

Before testing the measurement and structural model some preliminary data analyses are performed to cope with following issues: missing data, non-response bias, multicollinearity, common method variance (CMV).

Given the recent call of handling missing data issue with different approaches than simple pair-wise and list-wise deletion (Newman, 2014), we decided to check the conditions for applying Full Information Maximum Likelihood (FIML) estimation technique, which is strongly suggested as treatment for missing data in structural equation modeling (Enders & Bandalos, 2001). Under missing completely at random condition (MCAR) the FIML estimation is unbiased and efficient (Enders & Bandalos, 2001; Newman, 2014).

To test for missing patterns mechanism we employed Little's MCAR test, the result supported the presence of MCAR mechanism given there are weak evidences to reject the MCAR null-hypothesis of the test ( $\chi^2(149) = 164.09$ ,  $p = .19$ ); then we applied FIML as missing data treatment.

In order to control for non response-bias we employed late respondents' firms as surrogates for non-respondents (Goode, Lin, Tsai, & Jiang, 2015) and the t-test displayed no significant differences, suggesting that non-response bias was not an issue in this study.

The multicollinearity is tested with two steps. First we verified that all the EVA scores were above 0.5, second the VIF scores are computed and they are in a range between 1.38 and 1.59 safely below the suggested threshold of 5 (Hair, Sarstedt, Ringle, & Mena, 2012).

From the beginning of data collection we managed to control the CMV issue following some best-practices (Woszczynski & Whitman, 2004) such as assuring anonymity to the respondents, avoiding items' social desirability, demand characteristics, and ambiguity (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Once data were collected we test for common method bias employing Harman's single-factor test (Podsakoff et al., 2003; Woszczynski & Whitman, 2004); the variance explained by the first single factor in the un-rotated factor matrix was 40,1% below the 50% threshold. Thus common method bias was not a serious threat to the study validity.

#### *4.3.4. Measurement model*

The measurement model was also tested in terms of reliability, convergent validity, and discriminant validity. Reliability was assed through the analysis of the Cronbach's alpha (CA) and the Composite Reliability (CR) scores, all above the suggested threshold of 0.7 (Hair, Black, Babin, & Anderson, 2010), Moreover the items' loadings are almost all above 0.7 a part from two factors that are anyway above 0.6, a threshold representing a significant loading given the sample size (Hair et al., 2010).

All the average variances extracted (AVE) exceed the suggested threshold of 0.5 supporting convergent validity (Fornell & Larcker, 1981) together with the results

regarding CR above 0.7 and items loadings above 0.6 (Hair et al., 2010). Discriminant validity was assessed verifying that the the squared root of AVE are higher than any other the inter-constructs correlation (Fornell & Larcker, 1981) and each items outer loading on its assigned construct was greater than all the possible cross-loadings on other constructs (Farrell, 2010).

Finally, Confirmatory Factor Analysis (CFA) displays adequate fit indexes, suggesting goodness of fit of the measurement model:  $\chi^2$  of 365.36 with 199 df and CFI=0.95; TLI=0.94; RMSEA=0.067; SRMR=0.059; p=0.000.

[Table 4.3 here]

#### **4.4. Findings**

##### *4.4.1. Structural model*

Given the aim of verifying theoretical hypotheses derived from literature, this study employs correlation-based structural equation modeling (CB-SEM), which is more suitable in theory testing in cases of not too complex model, with sufficiently large numbers of observations (Hair, Hult, Ringle, & Sarstedt, 2014).

The model results (see Fig. 2) show that the model has a good fit with data:  $\chi^2$  of 374.79; df=203; CFI=0.95; TLI=0.94; IFI=0.95; RMSEA=0.065; SRMR=0.072; p=0.000.

Following the order of the hypotheses derived from literature, our model confirms that TO is strongly and significantly associated with firm performance (H1:  $\beta = 0.60$ ;  $p < 0.001$ ). The H2 is a central hypothesis for this study, given it suggests a positive association between employing SM in technological and solutions' information sensing and responding capabilities. In the previous literature the employment of SM, intended only as technological tools on which finding technological and solutions' information, had shown a negative effect. Instead this study focuses

on SM analytics, as tools and activities to manage the complex and fragmentary social media data to obtain information able to support TO. The positive association between SM analytics and TO finds significant support in our structural model (H2:  $\beta = 0.21$ ;  $p < 0.001$ ). Another interesting finding of this study regards the importance of changing organizational structure in order to better integrate the two functions more involved in the actual digital transformation context: Marketing and IT. First Marketing/IT integration is positively associated with the SM analytics deployment (H3:  $\beta = 0.37$ ;  $p < 0.001$ ) and with TO (H4:  $\beta = 0.16$ ;  $p < 0.01$ ) because both these functions are in charge of collecting, filtering, and interpreting the relevant digital data about external technological changes. Therefore, Marketing/IT integration is also positively associated with the degree of digital analytics skills (H5:  $\beta = 0.47$ ;  $p < 0.001$ ) because they have a cross-functional nature. Finally, digital analytics skills is positively associated with the degree of SM analytics deployment (H6:  $\beta = 0.51$ ;  $p < 0.001$ ), given the specific skills needed to deploy such activities.

[Figure 4.2 here]

#### 4.4.2. *Serial multiple mediation analysis*

To analyze the structure and significance of the mediations, which emerge from the research model, we decided to analyze the serial multiple mediation model (Hayes, 2013) that links all the constructs (except firm performance) to TO, and also the model that links all the constructs (including TO) to firm performance (FP).

Employing SPSS PROCESS script (Hayes, 2013) we analyzed both the serial multiple mediation models. The first model starts from the only one exogenous construct of Marketing/IT integration (MII) and arrives to TO via the other constructs of digital analytics skills (DAS) and SM analytics deployment (SMAD). Then we analyzed the other model that starts from MII, passing through DAS, SMAD, and OT and arrives to FP.

The results (see Table 4.4) supported the presence of the mediations derived from the research model and the non significance of the paths not founded in the literature.

The standardized indirect effects are reported with the bootstrapped confidence intervals calculated with 5000 samples iterations.

In the serial mediation model, with TO as outcome, none of the bootstrapped confidence intervals contain zero suggesting that all the indirect effect were significant.

In the second serial mediation model, with FP as outcome, three indirect effect were not significant; all of them do not provide the presence of TO as mediator of their relationship with FP. The other indirect effects, which are significant, all provide paths via TO to reach FP. These results support the findings of the structural model. Therefore, these empirical evidences confirm the absence of other possible paths not founded in the literature and hypothesized in the research model.

[Table 4.4 here]

## **4.5. Discussion and conclusion**

### *4.5.1. Theoretical implications*

From a theoretical point of view this study contributes to existing literature in several ways.

First it contributes to SM literature introducing the TO theoretical construct in the debate about the role of SM technologies as means to collect technological-related information. Then it contributes by providing strong and significant empirical evidences of the importance of SM in searching technology-related solutions' information; this contrasts with previous research findings. The discrepancy may depend by the previous focus only on "SM tools" employment, without investigating the

fundamental role of SM analytics to make sense of the complex, informal and fragmentary SM data. From a theoretical point of view this study disentangles the specific role of SM analytics from the more general idea of employing SM as source of solutions' information.

The empirical results of this study, compared with the divergent ones of previous literature, suggest that SM technology are not enough to support the understanding of technological changes because of the complexity of SM data. Then analytics tools and activities have to be deployed to make sense of SM data and support the sensing and responding organizational capabilities related to technological developments and changes.

Moreover, the study contributes to TO literature by suggesting the importance of cross-functional collaboration in sustaining TO. Especially in the actual context of digital transformation, it becomes central the integration of Marketing and IT functions. Both of them contain specific knowledge and competences that have to be integrated to develop technology-related sensing-and-responding capabilities.

#### *4.5.2. Managerial implications*

The present study also highlights some interesting managerial implications. First it corroborates the importance of SM data and tools as managerial sources of information. It also supports the role of SM data in sensing and responding to technological developments. Therefore, this study points out the the importance of digital analytics activities, and organizational digital analytics skills, as fundamental antecedents of TO. Both these aspects are strongly connected with the development of cross-functional integration between Marketing and IT functions. Then another interesting insight for managers is to prioritize the development of Marketing/IT integration and collaboration, given the complexity, which has already emerged in previous literature, of developing cross-functional projects related to these two functions (such as CRM projects). Both these functions are repositories of important knowledge and capabilities (technological, analytical...) that have to be integrated to cope with the increasing digitalization. The risk of not developing such

integration is that the strong differences between the two functions, in terms of goals and backgrounds, prevent the development of the necessary knowledge and capabilities to sense and respond to technological changes.

The above-mentioned aspects have to be prioritized in managerial agenda, in order to effectively compete in the actual scenario of digital transformation and fast technological changes.

#### *4.5.3. Limitations and future research*

Despite its contributions to an important heretical and managerial debate about the role of SM, this study is constrained by some limitations.

First of all, it relies on survey methodology based on the collection of perceptual data by a single key informant for each firms; even if considerable efforts were undertaken to ensure the validity of the study and to avoid common method variance, the complete absence of potential biases cannot be assured. Given the importance to check for inter-rater reliability future research have to address the issue collecting more than one survey for a single firm. Moreover, in order to support the generalizability of the study there is the necessity of triangulate the result with other source of data (i.e. case studies), given the limitation of perceptual data.

Further researches should also address theoretical issues, more than methodological limitations, such as the external environmental conditions that moderate the effects of SM analytics over TO and the role of other digital sources technological-related information. Finally, this study focuses on Marketing and IT functions, as the most involved in these process of sensing and responding to technological changes employing SM. Future research should also consider the role of collaboration and integration with other important functions, which are increasingly challenged by the digitalization, such as production, operations and supply chain.



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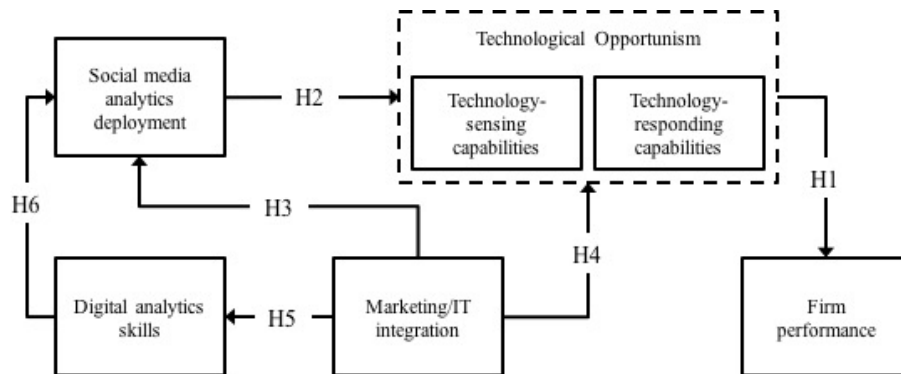
## Tables and figures

**Table 4.1.** Evolution of TO literature

Authors (years)	Technology-related theoretical construct	Antecedents	Outcomes
Nyström (1979)	<b>Technically-oriented:</b> search within technology areas for product ideas based on new technical principles.	Not considered.	Companies technically-orientated displays high level of innovation.
Cooper (1984)	<b>R&amp;D orientation:</b> orientation and commitment to new product program.	Not considered.	Successful NPD programs in terms of sales and profit generation and success of the new product.
Gatignon & Xuereb (1997)	<b>Technological orientation:</b> ability and will to acquire a substantial technological background and use it in the development of new product.	Not considered.	In highly dynamic market the technological orientation increase the innovative product performance (radicalness, advantage, costs).
Srinivasan, Lilien & Rangaswamy (2002)	<b>Technological opportunism:</b> the firm's capabilities in sensing and responding to new technology developments	Technological turbulence, adhocracy and clan culture, focus on future, and TMT advocacy.	New technology adoption.
Zhou, Yim & Tse (2005)	<b>Technological orientation:</b> commitment to R&D, acquisition of new technology, application of latest technology	Not considered.	TO positively affect tech-based innovation that have a positive impact on performance.
Garrison (2009)	<b>Technological opportunism:</b> organizational trait providing firms the capability to sense and respond to new technologies in the anticipation of creating sources of competitive advantage.	Organizational size.	New technology adoption.
Sarkees (2011)	<b>Technological opportunism:</b> use of firm resources to actively scan markets for disruptive discoveries that will change the way firms do business	Not considered.	Revenue, profit, and market value.
Voola, Casimir, Carlson, & Agnihotri (2012)	<b>Technological opportunism:</b> actively sensing appropriate technologies and quickly responding to technological developments.	Not considered.	TO positively moderates the relationship between market orientation and e-business adoption.

Chen & Lien (2013)	<b>Technological opportunism:</b> ability to understand and acquire knowledge about new technology developments and the willingness and ability to respond to identified new technologies.	Not considered.	Firm performance (NPD success rate, profitability, sales growth, market share)
Lucia-Palacios, Bordonaba-Juste, Polo-Re-dondo, & Grünhagen (2014)	<b>Technological opportunism:</b> capability to acquire, absorb, and assimilate internal and external knowledge and market information about new technologies in order to respond to the opportunities and/or threats that can appear.	Not considered.	IT adoption, IT diffusion, firm performance.
Lucia-Palacios, Bordonaba-Juste, Polo-Re-dondo, & Grünhagen (2016)	<b>Technological opportunism:</b> sensing and responding to the technological context	IT use (e.g. Extranet, Intranet, e-commerce, CRM...), IT human capital, IT vendor support.	Not considered.

**Fig. 4.1.** Research model and hypotheses





**Table 4.2.** Constructs, items, and sources

Construct	Items #	Scale items (item loading)	Source
Social Media analytics technology-related deployment	SMAD 1	We habitually use Social Media analytics tools to collect information about technological changes. (0.81)	Developed for this study
	SMAD 2	Data from Social Media analytics are crucial in supporting technology development-related activities. (0.85)	
	SMAD 3	We rarely employ data from Social Media analytics to support forecasting about technological changes. (R) (0.62)	
	SMAD 4	Decision-making about technological developments is supported by data from Social Media analytics. (0.87)	
Marketing and IT integration	MII 1	Marketing is involved with IT in setting new project schedules. (0.87)	Adapted from Peltier et al. (2013)
	MII 2	Marketing is involved with IT in setting new project goals and priorities. (0.90)	
	MII 3	Marketing is involved with IT in generating new project ideas. (0.92)	
	MII 4	Marketing and IT frequently discuss the quality of the data system. (0.74)	
Digital analytics skills	DAS 1	Our people are very good at identifying and employing the appropriate social media analytics tool given the problem at hand. (0.86)	Adapted from Germann et al. (2013)
	DAS 2	Our people master many different social media analytics tools and techniques. (0.89)	
	DAS 3	Our people can be considered as experts in social media analytics. (0.90)	
Technological opportunism  (Technological-sensing TO 1 – TO 3)  (Technological-responding TO 4 – TO 7)	TO 1	We are often one of the first in our industry to detect technological developments that may potentially affect our business. (0.74)	Adapted from Srinivasan et al. (2002) and Homburg et al. (2007)
	TO 2	We actively seek intelligence on technological changes in the environment that are likely to affect our business. (0.70)	
	TO 3	We periodically review the likely effect of changes in technology on our business. (0.69)	
	TO 4	We respond rapidly if something important happens with regard to technological changes. (0.81)	
	TO 5	We quickly implement our planned activities with regard to technological changes. (0.79)	
	TO 6	If they do not lead to the desired effects, we are fast at changing the activities related to technological changes. (0.83)	
	TO 7	This firm lags behind the industry in responding to changes about technological changes. (R) (0.84)	
Firm performance		In the last three years relative to your competitors, how has your business unit performed with respect to:	Adapted from Homburg et al. (2007)
	FP 1	Achieving the desired profit and revenue level?* (0.89)	
	FP 2	Achieving the desired growth?* (0.91)	
	FP 3	Achieving/securing the desired market share?* (0.87)	
	FP 4	Over the last three years relative to industry average, how has your firm performed with respect to return on sales?° (0.76)	
		* Seven-points rating scale anchored by “clearly worse” [1], “competition level” [4], and “clearly better” [7]	
		° Seven-points rating scale anchored by “clearly worse” [1], “industry level” [4], and “clearly better” [7]	

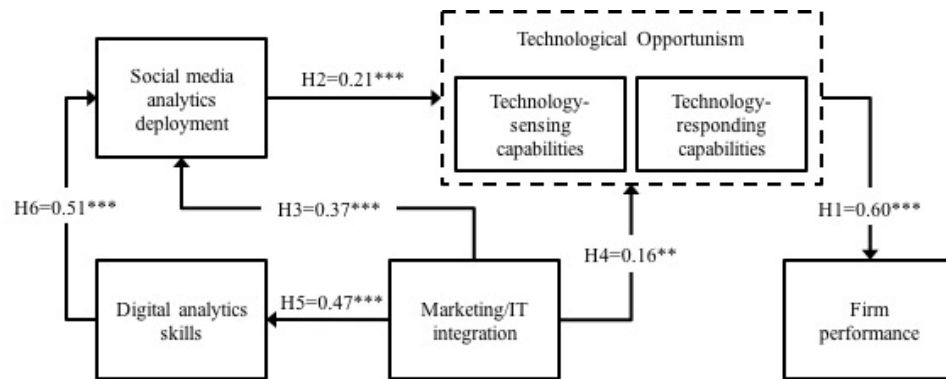
**Table 4.3.** Assessment of constructs' convergent and discriminant validity

Constructs	M	SD	CR	CA	AVE	1	2	3	4	5
1. Social Media analytics deployment	4.26	1.53	0.89	0.87	0.68	<b>0.82</b>				
2. Marketing and IT integration	4.48	1.65	0.93	0.93	0.76	0.54	<b>0.87</b>			
3. Digital analytics skills	4.78	1.43	0.96	0.96	0.88	0.44	0.42	<b>0.94</b>		
4. Technological opportunism	4.86	1.21	0.93	0.93	0.65	0.54	0.49	0.46	<b>0.81</b>	
5. Firm performance	4.81	1.12	0.92	0.92	0.74	0.29	0.29	0.23	0.44	<b>0.86</b>

1. M=mean; SD=standard deviation; CR= Composite reliability; CA= Cronbach's alpha; AVE=average variance extracted.

2. Numbers on the diagonal are the square root of AVEs. The other numbers are correlations among constructs.

**Fig. 4.2.** CB-SEM model



Fit indexes:  $\chi^2$  of 374.79; df=203; CFI=0.95; TLI=0.94; IFI=0.95; RMSEA=0.067; SRMR=0.072; p=0.000

# of cases =251 # of usable responses=184; \*p<0.05; \*\*p<0.01; \*\*\*p<0.001.

**Table 4.4.** Indirect effects

Total effect			Direct effect			Indirect effects			
Path	Coefficient	t-value	Path	Coefficient	t-value	Path	Point estimate	Bias corrected bootstrap 95% confidence interval	
								Lower	Upper
MII->TO	0.40***	6.6	MII -> TO	0.21**	2.96	Total	0.23	0.14	0.34
						via DAS	0.09	0.02	0.18
MII->FP	0.19**		MII -> FP	0.02°	0.22	via DAS->SMAD	0.06	0.03	0.10
						via SMAD	0.08	0.03	0.17
						Total	0.17	0.09	0.27
						via DAS->SMAD	0.04	-0.04	0.12
						via DAS->SMAD	0.01	-0.03	0.05
						via DAS->TO	0.03	0.01	0.08
						via DAS->SMAD ->TOP	0.02	0.01	0.05
						via SMAD	0.01	-0.04	0.08
						via SMAD->TO	0.03	0.01	0.07
						via TO	0.09	0.03	0.17

1. Bootstrapping of the 95% confidence interval based on 5000 samples

2. \* p<0.05; \*\*p<0.01; \*\*\*p<0.001; °not significant;